Holistic Integrated Process CONtrol

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Preface

Development of the holistic process management system has required close co-operation among experts in a variety of fields, e.g. economic, environmental and process modelling, multi-objective optimisation and model based control theory. In addition to this, the HIPCON project owes a lot to its two industrial case studies, acting as important demonstration sites for the project results. The following organisations and persons have contributed to the work in HIPCON.

IVL
Swedish Environmental Research Institute
Jonas Röttorp
Erik Furusjö
Magnus Andersson
Åsa Nilsson
Magnus Rahmberg
Mats Ek
Sara Nilsson
Klara Larsson
Anders Björk
Cajsa Hellstedt
Christian Junestedt
Mats Almemark
Ulrika Bark
Ann-Beth Antonsson
Elisabet Kock

Uppsala University
Division of Systems and Control
Prof. Bengt Carlsson
Prof. Alexander Medvedev
Magnus Evestedt
Mats Ekman
Björn Halvarsson
Pär Samuelsson
Linda Brus

LSE
London School of Economics and Political Science
Prof. Henry Wynn
Ron Bates
Sergey Shybayev

CTI
Computer Technology Institute
Prof. Robert E. King
Anna Stathaki
Aggeliki Prayati
Melina Gerbesioti
Prof. Fotis Koumboulis
Padelis Isaias

IMCG Ltd
Ian Napier

SSAB Oxelösund
Kim Kärsrud
Mathias Thorén
Lars Göransson
Jens Jacobsen
Sirkka Persson
Katarina Pein
Bo Sundelin
Daniel Widlund
The laboratory personnel

Stockholm Vatten AB
Berndt Björlenius
Anders Finnsson
Tommi Vornannen
Johan Ståhl
Michael Medoc
Anders Paulsson
Lars Storm
The laboratory personnel

Summary

The HIPCON project was created with the idea of developing methodology and a prototype software-package that enables production management accounting for:

- **Product quality**
- **Economical performance**
- **Environmental values**

This is achieved in an integrated approach. It is expected that the future production need to go in this direction, partly due to the increased attention to environmental impact of industrial production. An integrated approach is to avoid sub-optimisation. The software package is a real-time software with an extensive functionality covering:

- **Monitoring**
- **Advanced control**
- **Simulation**
- **Multi-objective optimisation**

The combination of the wide range of functions accounting for product quality, economical and environmental values makes the HIPCON software package unique.

One of the main objectives for the project was to demonstrate the added value of implementing the software at real production processes in full scale. The case study plants in the project were SSAB Swedish Steel in Oxelösund and Henriksdal wastewater treatment plant situated in Stockholm. These companies have also contributed in an important way with real production issues for the project to work on and by generating real process data for modelling.

At SSAB the HIPCON project was focused on the production chain from coke production and blast furnace to the steel making process including casting. Several successful results have been achieved from the project. An important feature in the steel making process is to remove the sulphur from the iron. Analysing the historical data, it was shown that the dosage of the desulphurisation reagent (calcium carbide) could be optimised, since most of the steel batches used more chemical than needed.

A process model that describes the optimal dose was developed and implemented in the HIPCON software in full scale production. The implementation has resulted in cost savings in the range of 5-8 million SEK/year due to reduced calcium carbide usage. The improved control has also resulted in a more uniform iron sulphur content. Another example from SSAB is a simulation model for the whole production plant that was developed. The model is based on a combination of mass- and energy balances and empirical correlations and estimates. It includes commodities, energy, products, by-products, pricing and environmental performance. Currently this model is used at SSAB to simulate different scenarios and to find out the best operation conditions given certain process states.

A model-based slopping detection system for the steel converter process was developed and successfully tested on process data at SSAB, correctly and timely recognizing 80% of slag overflow occasions. The system uses slag level estimation based on a signal from a microphone located in the off-gas funnel and a recursively updated model describing the relationship between off-gas flow rate, pressure and slag level estimate.

At the wastewater treatment plant Henriksdal several different objectives were identified. One of the most important aspects was to reduce the usage of precipitation chemicals. The precipitation chemical is mainly added to remove phosphorus from the water. However, it is

difficult and quite expensive to measure the phosphorus content in the incoming wastewater. In the HIPCON project soft sensors were developed that estimates the concentration of phosphorus, nitrogen and COD in the incoming water as a function of parameters that are relatively easy to measure, such as suspended solids, conductivity and pH. The soft sensors turned out to be very reliable and were installed at the plant for monitoring. Using the soft sensors for control of the dosing of precipitation chemical can potentially reduce the use of precipitation chemical about 30%, which corresponds to direct cost savings of 630 000 SEK/year. Less usage of chemicals will also improve the sludge quality since the ferric sulphate being used contains some heavy metals.

Another important objective for the treatment plant was to minimise the usage of energy. The largest single unit energy consumer in the activated sludge plant is the aeration of the biological process. In the HIPCON project an advanced control strategy for the aeration using a variable aeration volume was developed, implemented and validated in a pilot plant with the same configuration as the full scale plant. The data from the pilot plant experiment indicates that great savings (in the order of 30%) in energy consumption is possible without decreasing the effluent quality. Energy saving in the same order of magnitude at the Henriksdal wastewater treatment plant would imply a yearly saving of about 2 million SEK.

An Industrial Reference Group (IRG) has followed the project and has given very useful feed back throughout the project. For some of the industrial partners new projects have been initiated. In order to meet future demands on software upgrades, support etc the consortium has started the work on setting up a legal entity, with the main task to use the research results on the commercial market.

Contact information

Visit the project web site **www.hipcon.org** for up-to date information about the project. For further information, contact the project manager at IVL, Jonas Röttorp (jonas.rottorp@ivl.se, +46-8-59856300)

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1 Introduction

1.1 Background

The HIPCON project is a European Union 6th framework NMP priority STREP with contract number 505467-1 with 3 years duration from January 2004 to December 2006.

The background of the project is the notion that process industries in today's highly competitive global market must reconsider their production control policies and strategies if they are to achieve sustainable production and increase their competitiveness. In order to attain sustainable and economically efficient production, it is necessary to take a holistic view of process control and management. This can only be accomplished by integrating consideration of product quality, process economy and environmental impact in the next generation process control and optimisation systems.

1.2 Objectives

The aim of the HIPCON project was developing methodology and technology to facilitate transformation of the European industry to adapting holistic process management from a life-cycle perspective. In order to demonstrate the results and measure advantages a prototype software platform was developed. The system is to be implemented and demonstrated at the two case study industries.

The HIPCON project aims at developing methodology and technology for holistic process management from a life-cycle perspective. The project results will support long term transformation of European industry and promote increased competitiveness and eco-efficiency of the industries. The specific aims of HIPCON are to:

- Develop new parameters for economic and environmental impact of the processes on company and societal level.
- Develop process control and modelling methods for industrial production processes covering product quality, economic and environmental impact of the processes.
- Integrate performance indicators from different disciplines for holistic process management.
- Identify conceptual models and control objectives for the industrial cases. Successful modelling for all industrial cases, linking process status together with economical, environmental and quality performance.
- Produce prototype computer code integrating mathematical models from different disciplines and control strategies for development of a holistic process management system.
- Estimate performance improvements from a holistic viewpoint in all industrial cases.
- Disseminate the scientific results through scientific publications and conference presentations.
- Disseminate the results to relevant European industrial sectors through industrial take-up activities such as an industrial reference group, company visits and industrial seminars.

2 Software architecture and functionality

2.1 System specification

The proposed system architecture, as shown in Figure 1, is a distributed network comprising distributed Agents that are available to support run-time process control as well as off-line simulations. The On-line Subsystem (ONS) consists of Agents linked to the Data Base (DB) performing all the on-line functions. The off-line Subsystem (OFS) refers to the cluster of off-line models that are useful for simulation purposes and Scenario-Based Reasoning.

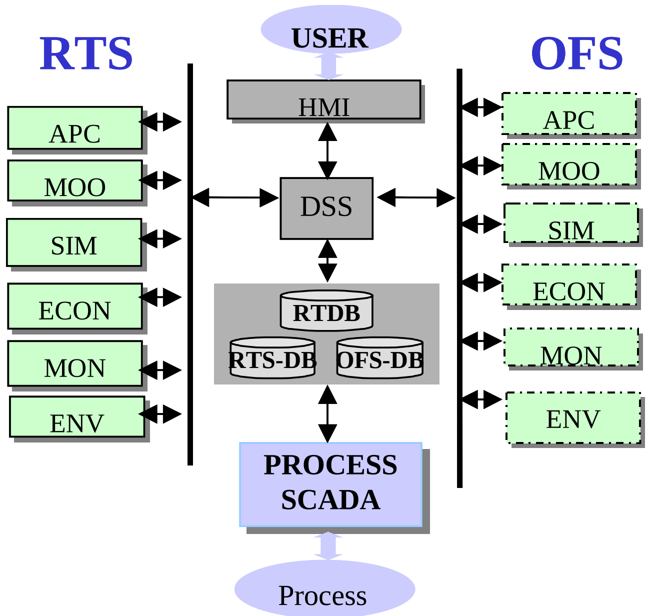


Figure 1. System architecture

The system incorporates a model DB and a DB for the off-line subsystem. These are repositories of the process modes, data and parameters required by the distributed modules.

2.1.1 The Proposed Decision Support System

The core component of the process control system is a Decision Support System (DSS), responsible for run-time monitoring of the process, coordination of the system functional components and determination of a control strategy that will maximize the product quality and minimize production costs and environmental impact. Apart from run-time monitoring and coordination, the DSS is designed to support off-line design decisions by simulating different operational scenarios. Additionally simulation support allows the user to investigate alternative control strategies for improved performance under difficult or less efficient conditions.

Taking into consideration the possible behaviour that can be expected from a DSS, four behavioural categories were identified and included in the resultant DSS: request acceptance, information acquisition, data processing and decision making. Thus the principal functions of the DSS are to:

- Assist in configuring the parameters of the Agents at run-time.
- Support a user-friendly graphical user interface for monitoring and controlling the system.

- Manage the parameters of the Agents at run-time and off-line.
- Ensure normal operation of the overall process.
- Provide optimum set points for the process with respect to economic and environmental parameters.
- Process historical data on the performance of the overall system in order to assess its performance.

2.1.2 The Distributed Agents

As distributed process control has proved to be efficient and robust, the essential Agents of the system are defined as follows:

Advanced Process Control Agent (APC): This Agent is responsible for establishing the best control strategy in order to follow that the performance of controlled process is minimal with respect to economic and environmental constraints.

Multi-Objective Optimisation Agent (MOO): This Agent performs multidimensional optimisation with consideration to environmental and economic objectives and/or constraints. This agent provides the optimum operating points of the process and incorporates an array of methodologies that can be called upon to determine the best operating conditions.

Environmental Agent (ENV): The objective of this Agent is to model the environmental performance of the process by computing the environmental impact of the process, including both the upstream environmental impact of production used in the process and the downstream environmental impact associated with treatment of the waste products.

Economic Agent: **(ECON):** The objective of this Agent is two fold: to compute the projected economic performance of the process by taking into account economic factors and to provide corresponding information when specifying operating conditions of the process. Performance Indicators are estimated by ECON based on on-line and historical process data.

Process Monitoring Agent: **(MON):** This Agent is responsible for process monitoring including soft-sensing, sensor diagnostics, process fault/disturbance detection and identification by determining quality-related parameters of the process.

Simulation Agent (SIM): The role of this Agent is to perform simulation on the results of which the DSS will be able to infer strategies for improved control. Simulation scenarios are examined, holding different operating conditions and abnormal situations off-line on a separate platform. The SCEN agent, which exists only in the OFS, provides the SIM Agent with the necessary data (variables, parameters and time series) through a graphical interface in order to examine the behaviour of the process for various simulation scenarios.

2.1.3 Data management and acquisition

All Agents are linked closely to the Real-Time Data Base, which contains current and historical data in the existing database of the SCADA of the physical process, servicing all the distributed Agents with the data they require to execute their task as and when required. Acquired data is tightly coupled to each application and thus highly dependent on the existing process SCADA and the communications facilities it possesses. A non-real time Data Base is integral to the DSS and constitutes the repository of parameters and models required by the various Agents. The Supervisory Control and Data Acquisition System (SCADA) deals with the physical process interface, retrieving data from the process for further processing by the DSS.

2.2 DSS Architecture

The general architecture of the DSS is shown in Figure 2. The DSS consists of four basic elements, namely the control kernel and the interfaces to the various system components. The control kernel contains three major components: the daemon for coordinating the system, the scheduler for managing the Agents execution sequence and the watchdog for polling the critical variables and managing the alarms in the system. The daemon controls the reading and writing of data to the DB, the Agents execution and the user interaction with the system. For all three interactions an interface is defined, respectively the DB interface, Agent interface and HMI.

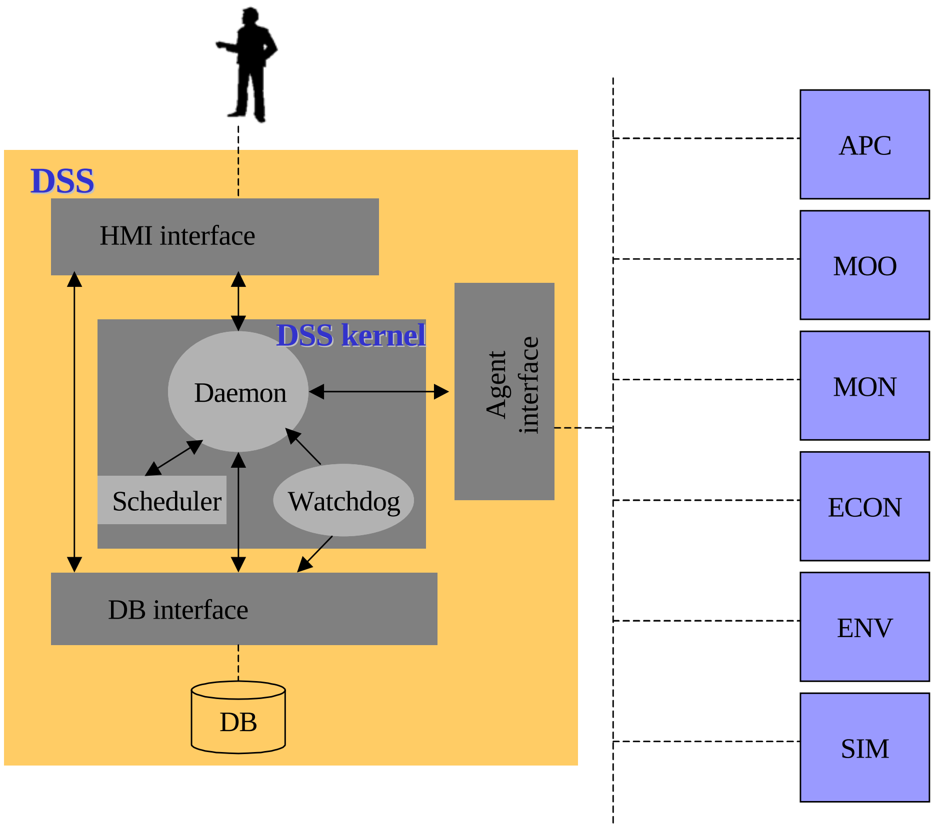


Figure 2. DSS architecture

A formal Unified Modelling Language (UML) system model is shown in Figure 3. The components of the DSS are described in more detail below.

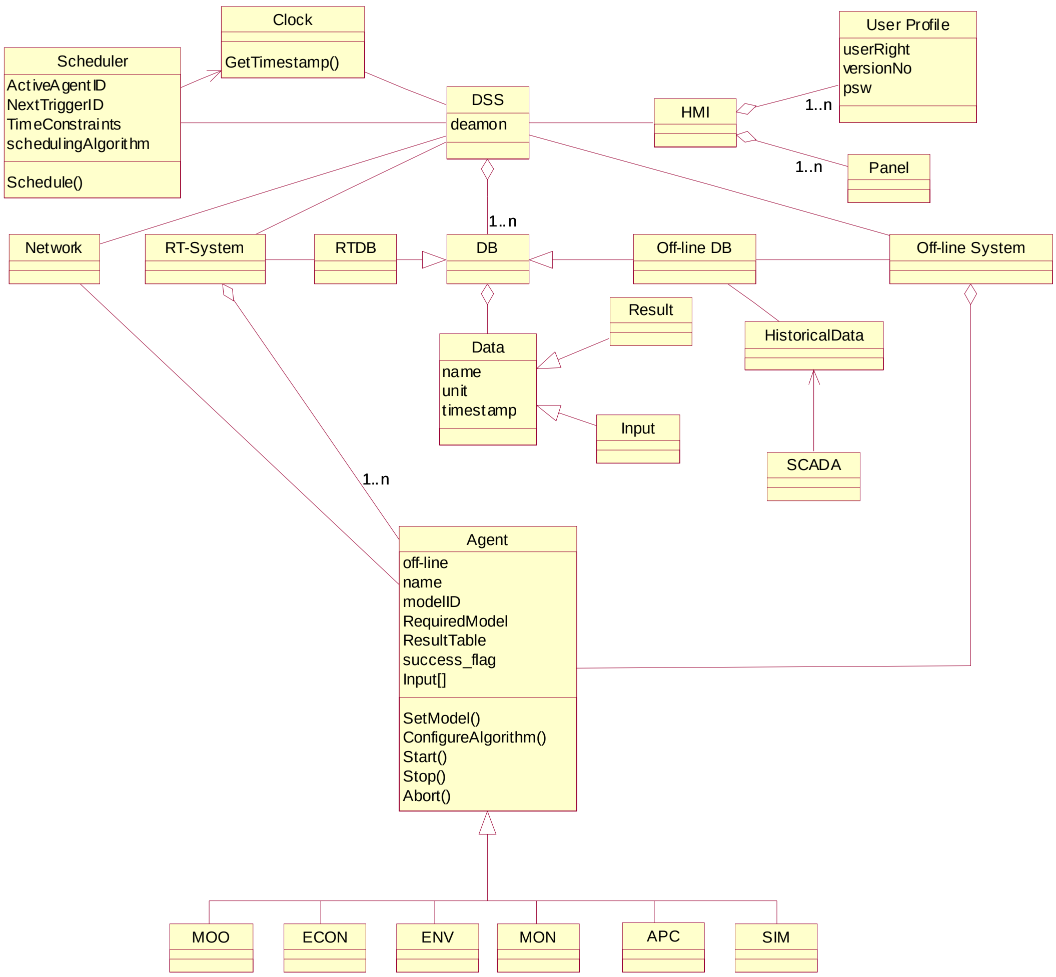


Figure 3. UML-based DSS architecture

2.2.1 Daemon

The daemon is the core module of the DSS and is responsible for managing, coordinating and controlling the overall control system. The daemon coordinates all the interfaces and the Agents execution, according to the following rules:

- triggers the MOO Agent at run-time, upon notification from the watchdog, indicating that an alarm situation has been detected and thus a new control strategy must be computed for the physical process. Since MOO requires data from the other Agents (ECON, MON, ENV, SIM), before execution of the MOO, the daemon must ensure that the required models have already been executed in these agents and the corresponding parameters required by the MOO are available.
- configures the Agents with the appropriate models as defined by the user during the configuration phase and executes the agent instances according to the schedule provided by the Scheduler. The results are saved in the DB and the graphical environment is provided with the user indicated parameters for visualization.
- in case an alarm is generated by the watchdog, the HMI notifies the user if manual mode operation is selected. Alternatively when in autopilot mode, a “red” alarm is treated automatically by executing the MOO Agent without further user interaction.

- triggers the APC Agent when a new operating point is specified by the user among optimum alternatives generated by the MOO Agent.
- maintains a log file of operational status that can be recalled for review upon user request.

2.2.2 Watchdog

The watchdog is responsible for polling the critical variables of the physical process and in case of alarm, generating discrete events in order that the MOO Agent is executed. Apart from checking the alarm limits, the watchdog is also responsible for tracking the critical variables in a "semi-alarm" region that is defined as a percentage of the alarm threshold, where a notification that the specific variable is approaching the alarm bounds is generated. The watchdog consists of a thread and interacts with the daemon in the following cases:

i. retrieves the critical variables from the DB and checking their values.
ii. notifies the user of alarm situations or when threshold values have been exceeded.
iii. triggers the MOO by calling the daemon. Once the daemon is notified about an alarm, the sequence of execution of the HMI and the MOO Agents is controlled by the daemon and the watchdog is reset. This means that the alarm events sequence is reset and the thread is reset.

2.2.3 Scheduler

Since distribution of tasks is considered in the original system architecture, the scheduling policy has one extra degree of freedom allowed by concurrency. However, considering alternate cases of implementation where only a single processor platforms is available instead of a multiplicity of distributed processors, a sequential schedule cancels this freedom and imposes one extra constraint on the scheduling algorithm. Therefore, two alternative scheduling strategies are defined to provide a static schedule according to the following parameters:

i. execution interval configured by the user for every Agent instance.
ii. preconditions for Agent execution i.e. precedence constraints.
iii. logical execution of the Agents i.e. when MON models generate outputs used for the execution of ECON and ENV or MOO must be triggered after all other Agent execution.
iv. Imposition of soft real-time constraints for the APC Agent at run-time.

The scheduling policy produces a feasible scheduling scheme, which is used by the daemon to trigger the corresponding Agents sequence.

2.3 MOO Agent

Multi-objective optimisation is an essential part of the system, carried out by the MOO Agent. This section describes the MOO functionality and its interaction with the DSS.

2.3.1 Description of MOO algorithm library

The main function of the MOO algorithm library is to provide a system that takes a problem description defined by the DSS and returns the optimal solution. The main issue with this system is that it is required to operate in real-time conditions. That is, the problem specification, submission to the optimiser, and resulting solution all need to be implemented as an automatic system that is guaranteed to produce a fast, meaningful result.

The GAMS modelling system was chosen as the numerical optimisation package at the heart of the MOO. The MOO formulates a HIPCON optimisation problem in the GAMS language, GAMS then determines the solution of the multi-objective optimisation problem and returns a result. This can then be read by the DSS for visualization and further processing.

The MOO library includes a data interchange utility, dss2gms, which translates the problem description from a file created by the DSS (a .moo file) to a file to be submitted to GAMS (.gms file). The .moo file is a problem description, generated by the DSS. The .gms file constitutes the input to GAMS. The utility has been developed in C and has been continuously developed throughout the HIPCON project to handle the following problem classes.

- Linear, polynomial, rational polynomial and power functions
- Real, integer or mixed integer problems
- Linearly constrained or unconstrained
- Scalar or weighted vector problems (one or many objective functions)

2.3.2 MMM: MOO Model Manager

In order to create a valid optimisation problem for GAMS to solve, the MOO must receive two sets of models that constitute both the objectives and the constraints of the problem. This is the task of the MMM (MOO Model Manager).

The model sets are composed of HIPCON Agent models selected by the user via the DSS. Because the user is free to select any combination of Agent models, the MMM must check that the model sets are consistent, for example by removing any unnecessary models that do not contribute to either the specified objectives, or the specified constraints of the chosen optimisation problem.

In order to achieve this, a standard modelling framework has been developed and applied to all the HIPCON Agent models. The modelling framework defines a set of allowable model classes from which all Agent models are derived and also provides the descriptive coding language used to express all Agent model instances. With all Agent models being expressed in a known form, the MMM can check and simplify an optimisation problem specified by the DSS prior to submitting it to GAMS to be solved.

2.4 Interface services

In this section the three basic interfaces of the DSS are outlined. These are the user interface, the DB interface and the interface to the Agents.

2.4.1 User interface

A Human-Machine-Interface (HMI), used for the graphical user interface, provides the following services:

i. Configuration of the Agent parameters: model type, input variables and execution interval.
ii. Modification of existing configured Agent instances.
iii. Graphical representation of the results from the configured Agent models execution.
iv. Graphical support for the user interaction with the Agent results.

v. User notification in case of alarm.

vi. Generate report with daemon interface events and actions, which is presented in an event log window.

vii. Specification of attributes for the simulation model and representation of results of the simulation process

viii. Specification of the operational scenarios and representation of results.

2.4.2 Agent Interface

The DSS-Agent interface is defined by the use of a wrapper, which is responsible for encapsulating the Agent-specific services in a standard DSS-Agent interface, as shown in the UML diagram in Figure 4.

For the different models that are configured to run on one Agent, multiple instances of the Agent are created by the DSS. A different model with its associated inputs is loaded from the model library to the corresponding Agent instance by the function SetModel().

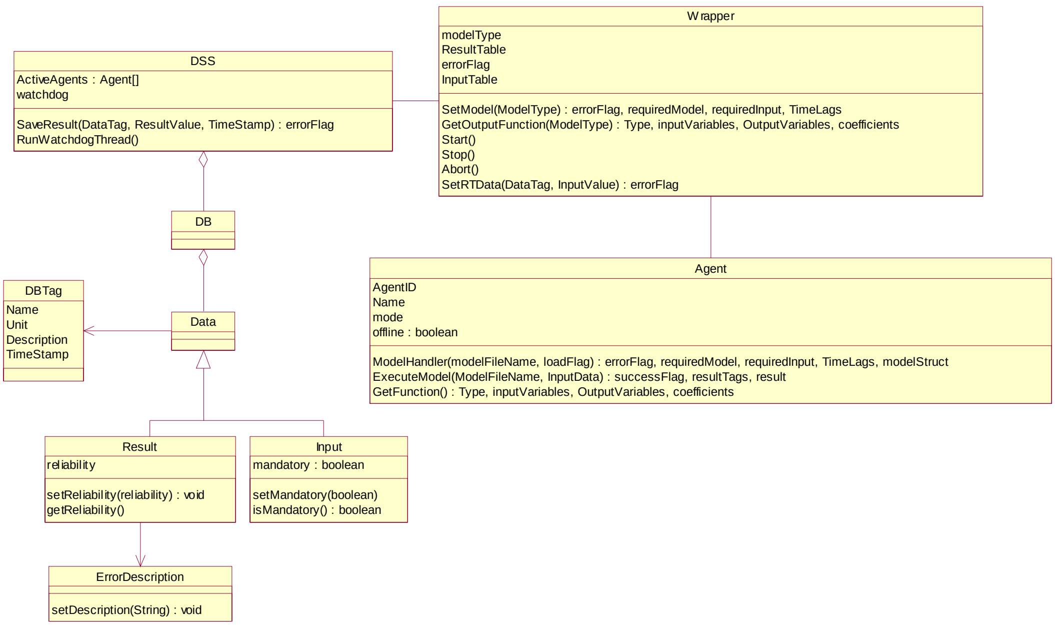


Figure 4. Wrapper interface definition

The second interface function defined is SetRTData (DataTag, InputValue), which is called to provided all data necessary to the configured Agent instance. The input data is assigned values by the DSS, which retrieves the corresponding data from the historical DB using the appropriate input tags and time lags for every model loaded, performing interpolation as needed. DataTag is a vector containing the input data tags and InputValue is a table with the values of the corresponding input data tags at the various time instances.

The Start and Stop functions are defined to execute the Agent instances according to the schedule generated by the Scheduler module. In case of abnormal operation, the Abort function is used to interrupt the execution of the active Agent instance. Under normal operation of the system, where the Agents run without pre-emption, the wrapper uses the SaveResult(DataTag, ResultValue) function to return results to the DSS once the Agent instance has finished its execution,. DataTag is a vector of Strings denoting the agent execution result data tag, while ResultValue is a vector of type double elements containing the corresponding result values.

The input required for the MOO Agent implies particularities that impose the need for additional constructs in the MOO interface, as well as in the wrapper definition. For all corresponding models computing the physical process parameters, objective functions must be provided as inputs to the MOO. To retrieve this information, the function GetOutputFunction() is defined.

2.4.3 Data Base Interface

The RTDB, historical DB and model DB are accessed for data required by the agents. The model DB holds tables with information for the Agents' available models, their correspon-ding input and output types, as well as their execution time and period. The following accesses to the DB tables are performed through SQL queries for the different DSS functionalities.

- At the configuration phase, the model DB is accessed to retrieve the available models for every Agent, as well as their corresponding information. The tables are also updated with the configured Agent instances and the historical DB data tags connected to the model inputs.
- At run-time, the daemon keeps track of model ids executed and accesses the historical DB for input data provision.
- The results of every configured Agent instance are saved in a separate DB table in order to avoid simultaneous accesses and conflicts. The results are consumed either for graphical representation or for other models' execution.

2.5 Implementation and testing

The DSS components and Graphical User Interface (GUI) have been implemented in Visual Basic with Microsoft Visual Studio v6.0, while the Agent algorithms were converted in dynamic link libraries with Distributed COM technology (DCOM dll) from packaged MATLAB modules. The models of the Agents residing in the model DB are .mat MATLAB models. Finally, the DB structure has been implemented in ORACLE and its interface to the DSS with SQL queries integrated in Visual Basic. One of the achievements of this project has been the seamless integration of software written in a multiplicity of languages.

The distributed system architecture allows for ready addition of additional Agents should other impact factors of the physical process prove necessary. The DSS design is flexible and the UML model open and adaptable for extension to cover applications of a different nature. The HIPCON System was tested with two driver applications, namely the Henriksdal wastewater treatment plant and a steel-manufacturing unit. The fact that the two applications are quite different with respect to their nature and performance parameters makes them adequate drivers in proving the robustness of the architecture and functionality implemented in the project.

3 Environmental and economical performance

Integration of process economics and environmental impact with product quality is a key objective of HIPCON. Conventional methods from the respective fields have been used, as described below. The novelty lies in the combination and integration of methods, adding extra dimension to the traditional process monitoring and control approach.

3.1 Environmental performance

The environmental models developed in HIPCON are based on Life Cycle Inventory (LCI) data. LCI models are accomplished by tracing backwards in the production chain of commodities, which are used in the process, and register e.g. energy consumption, emissions and wastes, preferably all the way back to the extraction of natural resources. Treatment of waste from the process is modelled correspondingly. Connecting the LCI-models to process measurements of used commodities and produced waste results in knowledge of the process' entire environmental impact, not just its direct emissions. Four impact categories are used to present the results of the environmental models:

- Acidifying Potential (AP), expressed as mol H^+.
- Eutrophication Potential (EP), expressed as kg O_2 demand of emitted oxygen depleting compounds.
- Global Warming Potential (GWP), expressed as kg CO_2 equivalents.
- Waste Indicator (WI), expressed as kg of waste produced that is not recycled or reprocessed.

3.2 Economical performance

3.2.1 Process economics

Production is a foundation concept in economics. An obvious potential benefit of an economic analysis of a production facility (plant) is to show how to yield the maximum output for the minimum cost. In order to move closer to this goal, accurate models of production cost, in relation to output yield and quality need to be developed.

In addition to the work presented elsewhere in this report models have been developed to monitor market price information, in the form of time series, for two main purposes: (i) to rank market prices according to their volatility, and (ii) to detect sudden changes in the underlying structure of the time series, indicating a large external market effect. However, these models are not implemented in the current version of the prototype software system.

It was also decided that the intended development of macro-economical models, e.g. modelling the impact of national economy on individual plant operation, should not be included in the first version of the system.

3.2.2 Production costs

The overall cost of production in a plant can be estimated by considering the costs and profits incurred in the following categories:

1. Raw material costs
2. Energy costs
3. Value of product (which is profit rather than cost)
4. Running costs / maintenance
5. By-product disposal costs

In general, when considering production costs in the HIPCON project, there are two main sources of data: process data and accounts data.

3.2.2.1 General construction of cost drivers

Cost drivers are functions of amounts (A) and prices (P), such that

$C = A \times P$

If amounts and prices vary over time, as is the case here, then the above equation can be re-written to be time-dependent:

$C(t) = A(t) \times P(t)$

so the cost is for a particular instant in time, t (instantaneous cost). To calculate costs over a time interval $\Delta t = [t1, t2]$ use is made of the integral:

$$C_{\Delta t} = \int_{t_1}^{t_2} A(t)P(t)dt$$

Note here that the price, P, may also depend on other quantities such as whether the amount exceeds the threshold limit (see section 3.2.2.2). These quantities may be constant or time-varying. If they are time-varying, they are sampled and averaged, possibly over several different time intervals, and then stored in the HIPCON real-time database (RTDB). Therefore, in order to construct cost models we need to consider time intervals Δt, related to the sampling frequency of the data which could be measured in seconds, hours, days, weeks or, in the case of certain price data, years.

3.2.2.2 Prices

Prices may be fixed (scalar) values, or functions of other quantities (e.g. time, volume). For example, one could be interested in the price charged to discharge certain chemicals into the environment. A standard functional form for the price is shown in Figure 5.

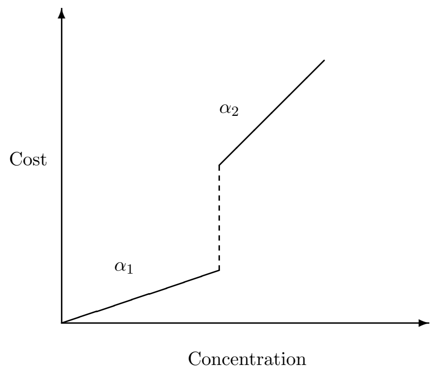


Figure 5. Typical cost function. The symbols {α_1, α_2} refer to the gradient of the two line segments and represent prices.

This is a discontinuous function with two phases. The first phase relates to the process when it is within target. For our example this means that the values of chemical concentration in the effluent are below given target values. The second phase represents the cost when these targets have been breached, and include a levy, or fine, for failing to meet the target, leading to the discontinuity.

3.2.2.3 Key performance indicators

For each case study, key performance indicators (KPI) have been selected to monitor the economic performance of the plant. Each KPI is constructed from a set of cost drivers that represent expenditure during plant operation. Further details are presented in sections 4.6 and 5.7.

4 Results of the WWPT case study

4.1 Introduction

A pressing need in urban WWTPs is improved performance, minimization of operational costs and environmental impact. To this end it is necessary to have close insight on the operation of each stage of the process that contributes to the end result. Due to the complexity and scale of such physical processes it is often infeasible to use trial and error methods to manage and control the process for they are costly, time consuming and may affect the environment adversely. To circumvent this problem it is necessary to obtain an understanding of the plant so that causes and effects are well understood.

4.1.1 Process description

The Henriksdal wastewater treatment plant (WWTP) treats sewage from about 700 000 persons. This means 2.8 m^3/s in average, but the flow rate and composition varies over the day and is dependant on weather conditions. The process contains sections of mechanical treatment (grid, sand trap and filter), chemical treatment (pre-precipitation + sedimentation and post-precipitation before the filter) and biological treatment (activated sludge and sludge digestion), cf. Figure 6. Activities in HIPCON have focused on the chemical and biological sections of the WWTP.

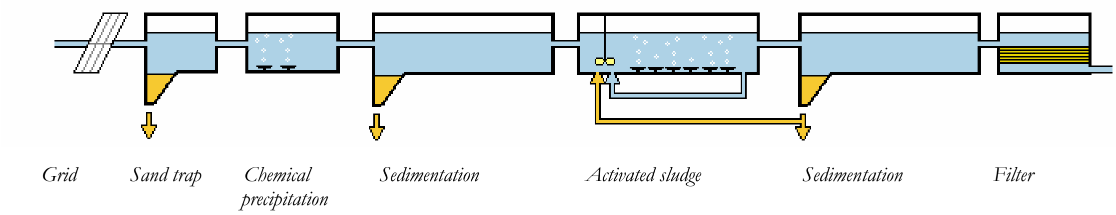


Figure 6. Process outline of Henriksdal WWTP, influent sewage to effluent water. Chemical and biological sludge is removed for further treatment, e.g. thickening and digestion (not shown).

The treatment result (effluent water) has to reach specified water quality levels on the content of phosphorus, nitrogen and organic matter. Phosphorus is mainly removed by chemical precipitation but also in the biological treatment. Nitrogen is removed in the activated sludge basins with the biological processes of nitrification and de-nitrification. Organic material is mainly removed in the activated sludge basins but also in the chemical precipitation due to flocculation.

4.1.2 Case study objectives

In addition to the overall HIPCON objectives, the case study of Stockholm Water had the following specific objectives:

- Creating models that describe the influence of possible control actions on treatment results and process operation costs.
- Comparing the environmental impact caused by the use of chemicals and energy, the production of waste material and discharge of treated water to the environmental impact caused by the discharge of untreated wastewater.
- Combining this into a common model that can be used on-line to control the process.

4.2 Modelling of influent composition and pre-precipitation

4.2.1 Soft sensors for influent composition

4.2.1.1 Introduction

The wastewater entering a wastewater treatment plant varies significantly, both with respect to amount, flow rate and composition, complicating the wastewater treatment process. To learn about the influent water and what effects it has on the following treatment steps it is most likely necessary to install extensive on-line instrumentation in the influent. However, a major problem is that the wastewater, and especially untreated wastewater, constitutes a very harsh environment for sensors. This significantly complicates on-line measurements many parameters and/or makes them impossible. Also, the sensors often are very expensive and maintenance intensive. One way to solve this problem is to use soft sensors. A soft sensor is a mathematical model that estimates the desired, often non-measurable, parameter using other measurable parameters. The soft sensor models make use of the fact that the levels of different contaminants are not independent of each other, and thereby that information about the composition of the water that is easily accessible (such as pH, conductivity, suspended solids (SS) and flow rate) contains information about more complex parameters, e.g. phosphorous, nitrogen and COD. Thus soft sensors can be used to estimate variables that are difficult to measure on-line from parameters that are less complicated to measure on-line, as illustrated in Figure 7.

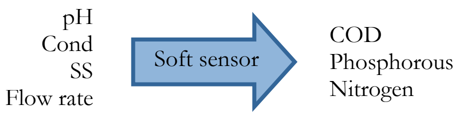


Figure 7. The concept of a soft sensor.

4.2.1.2 Sampling Campaigns

During five sampling campaigns more than 350 samples have been taken from the influent. The samples were one hour collection samples collected for 2 to 6 days, during summer, winter and autumn The samples collected during the sampling campaigns were analyzed on the lab with respect to concentration of COD, NH_4, N_{tot}, PO_4-P and P_{tot} [mg/L] and on-line data for conductivity, pH, flow rate and SS was logged for corresponding time periods.

4.2.1.3 Modelling methofology

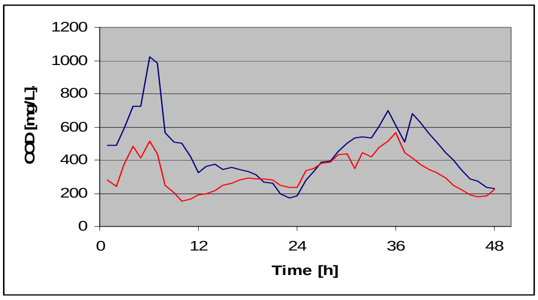
Two separate modelling methods have been attempted for this application.

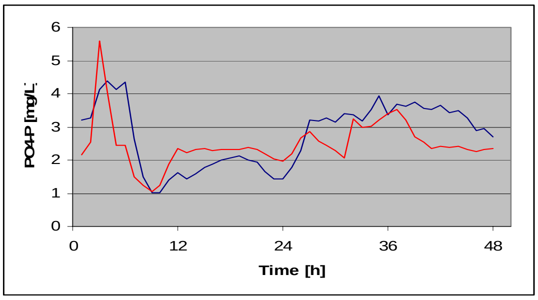
PLS (partial least squares) was used to fit soft sensor models for **COD, NH_4, N_{tot}, PO_4-P** and **P_{tot}**. PLS is a multivariate regression technique that finds a linear model that describes the parameters that are hard to measure in terms of other, measurable, variables (in this case conductivity, pH, flow rate and SS). One important advantage that comes with the use of PLS is that it also provides a tool for outlier detection, e.g. by determining so-called SPE and Hotelling´s T2 values for each new observation. These two parameters are estimate of how far an observation is from the model and limits that define normal conditions can be set.

The other modelling method used is recursive system identification with a nonlinear static black-box model. It was used to fit soft sensor models for **PO_4-P** based on information about the variables that are easier to measure. In short, a recursive prediction error method (RPEM) is applied with a (nonlinear) polynomial model. Since no a-priori knowledge of the system dynamics is required this approach is an example of non-physical modelling, commonly referred to as black-box modelling. The two most important input signals to the model were the pH value and the conductivity. Slightly better models were obtained if also the influent flow rate was included as an extra model input. It was found that including nonlinearities in the model improves the estimation performance.

4.2.1.4 The soft sensor models

Soft sensor PLS models for COD, NH_4, N_{tot}, PO_4-P and P_{tot} were calculated on data from the four first sampling campaigns. To evaluate how the soft sensors would work in reality, i.e. with unknown data, data from the fifth campaign was used for external validation. To illustrate the results from the external validation, diagrams showing measured values and by the soft sensors predicted corresponding values are shown in Figure 8 below.





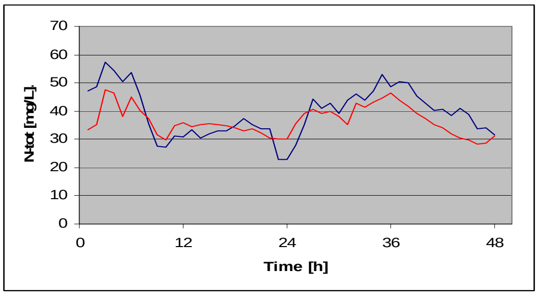


Figure 8. External validation of the soft sensors for COD (upper left), PO_4-P (upper right) and N_{tot} (lower left). The soft sensors were calculated on data from the four first sampling campaigns and validated with data from the fifth sampling campaign. The curve corresponding to the measured values is plotted in blue and the curve corresponding to the predicted values is plotted in red.

The above mentioned soft sensors were implemented in the HIPCON prototype in September 2006 and have been generating on-line predictions for monitoring of COD, NH_4, N_{tot}, PO_4-P and P_{tot} at Henriksdal WWTP. The outlier detection functionality of the PLS soft sensor models was also used on-line to provide a tool for estimation of model validity. This approach greatly increases reliability of the soft sensor predictions. An example with a time periods with a failing sensor providing input data is shown below. The failing sensor is immediately detected and the predictions flagged as unreliable.

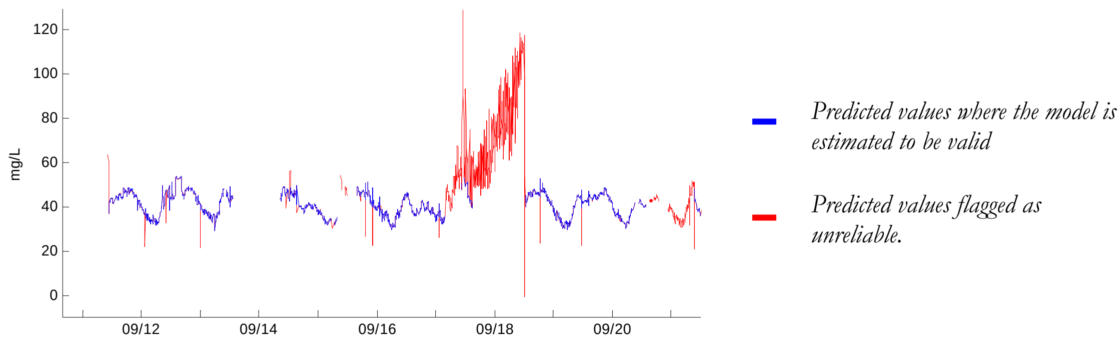


Figure 9. N_{tot} on-line predictions for 10 days (September 11-21), incoming water Henriksdal WWTP.

The nonlinear static black-box recursive system identification models were only developed for PO_4-P and had a slightly better performance than the PLS models for this end-poit. It should be noted that they do not give the prediction diagnostics discussed for PLS above.

4.2.1.5 Soft sensors for control of the precipitation chemical dose

A possible application for the soft sensors is to use them for control of the precipitation chemical dose at the pre-precipitation step. Today Henriksdal WWTP doses the precipitation chemical in the pre-precipitation step proportional to the flow rate of incoming water. A more intricate dosing strategy would most likely result in a decrease in precipitation chemical consumption and thereby a significant economical profit. For example, calculations based on historical data showed that a feed-forward controller based on the concentration of PO_4-P in the inlet would result in a decrease of use of precipitation chemical of **28%**, corresponding to a **yearly saving of 630 kSEK**.

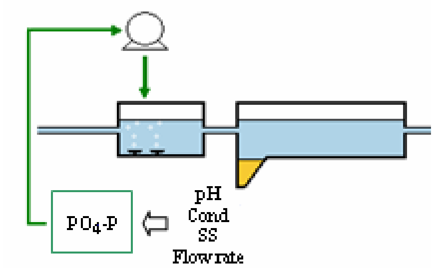


Figure 10 Feed forward regulation of $FeSO_4$ dose based on the soft sensor values for PO_4-P

4.2.2 Self-organizing networks

There are essentially two classes of models that can be used to describe a process quantitatively: microscopic and macroscopic. It is not often possible to determine microscopic (i.e. state) models that have the desired fidelity necessary for prediction and optimisation. In such cases use is made of macroscopic models (i.e. black box or input-output models) mined from normal operating records. Adaptive neural networks (ANNs) can be used to this end.

One class of neural networks that has proved very effective for both modelling and prediction are self-organizing networks which have an architecture very similar to that of classical feed-forward ANNs but differ in that they use clusters of polynomial neurons stacked in layers, each neuron involving only one pair of inputs instead of neurons with compression elements. Self-organizing networks are trained using inductive learning methods instead of deductive learning. Unlike classical neural networks, the architecture of the network is not specified *a priori* but evolves during the training procedure, successively increasing its complexity with each training/selection cycle by adding new layers while eliminating branches and interactions that do not contribute to the end result, until no further improvement is perceived. Self-organizing networks are the kernel of the Group Method of Data Handling or GMDH that was introduced by Ivakhnenko in the mid 1960's.

Self-organizing networks belong to the class of multilayered polynomial networks that have proved effective in practice for both modelling and prediction. The nodes of a self-organizing polynomial network are N-Adalines, i.e. Adalines with nonlinear pre-processors. The values of six synaptic weights completely define the non-linear transfer relationship of each neuron in the network which may involve a large number of neurons. The optimum values of these weights are computed iteratively using a fast learning algorithm that has been developed in the project.

Two salient features of this class of networks differentiate them from conventional deductive networks:

- Their structure evolves during training instead of being predefined. Thus there is no need to guess the number of layers and neurons in each layer of the network.

- Unlike ANNs, self-organizing networks cannot be over-trained, a desirable feature. To achieve this property, process input and output data sets are divided into three subsets: the Training, Selection and Evaluation Set. The algorithm automatically selects the subsets from data acquired from the process.

Self-organizing networks have been used to mine macroscopic models of the pre-precipitation sub-process that precedes the ASP. Having determined the causalities between the inputs and outputs of the process using knowledge mining techniques, self organizing networks have also been used to infer process measurements that would otherwise require prohibitively expensive and unreliable sensors from cheaper and more robust sensors that are readily available. This has led to a class of smart sensors in which self organizing networks are integrated that yield good fidelity at low cost. By way of example the results for two measurements *Ptot_out* and *PO4_Pf_out* of the pre-precipitation process are shown in Figure 11.

The inputs to the self-organizing dynamic neural network are the current measurements of *FLOW, Fe, TEMP, COD_in, P_tot_in, COND_in, CODf_in, NH4_Nf_in* and *SSf_in* and their past values.

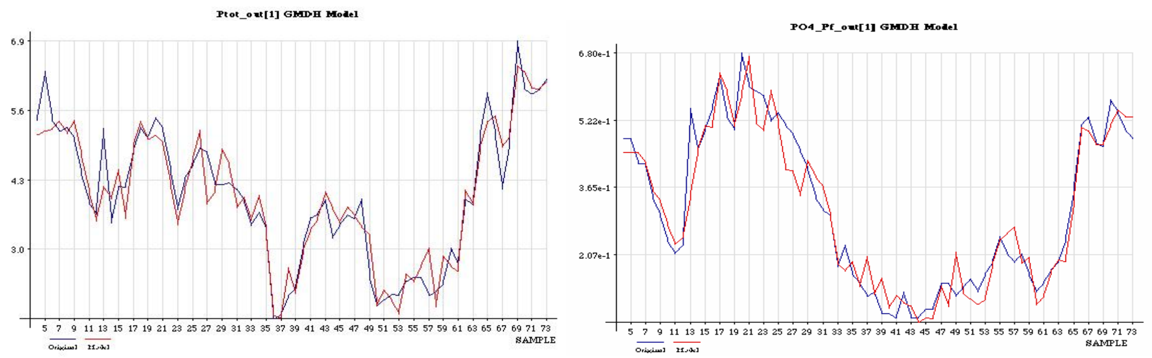


Figure 11. Self-organizing network models of Ptot_out (left) and PO4Pf_out (right). Blue lines are the actual measurements and red lines are the model results.

4.3 Control strategies

4.3.1 Improved control of aeration in biological treatment

The aeration of wastewater in biological treatment of wastewater (e.g. an activated sludge process) is fundamental both concerning energy consumption and treatment results. The aeration is hence a crucial variable to control in order to optimize a plant. A volume control strategy for the aerated compartments in an activated sludge process (ASP) has been developed. The main idea is to select the dissolved oxygen (DO) concentration in some of the compartments by estimating the load into the plant indirectly by the air flow rate in one of the DO controlled compartments. The strategy will increase the number of aerated zones when the load into the plant is high and decrease the number during low loads. This gives the potential to save aeration energy while still maintaining a high treatment capacity. A simplified version of the control strategy is shown in Figure 12. A detailed description of the control strategy can be found in the scientific publications by M. Ekman et al, [4] and [15] cf. section 6.2.

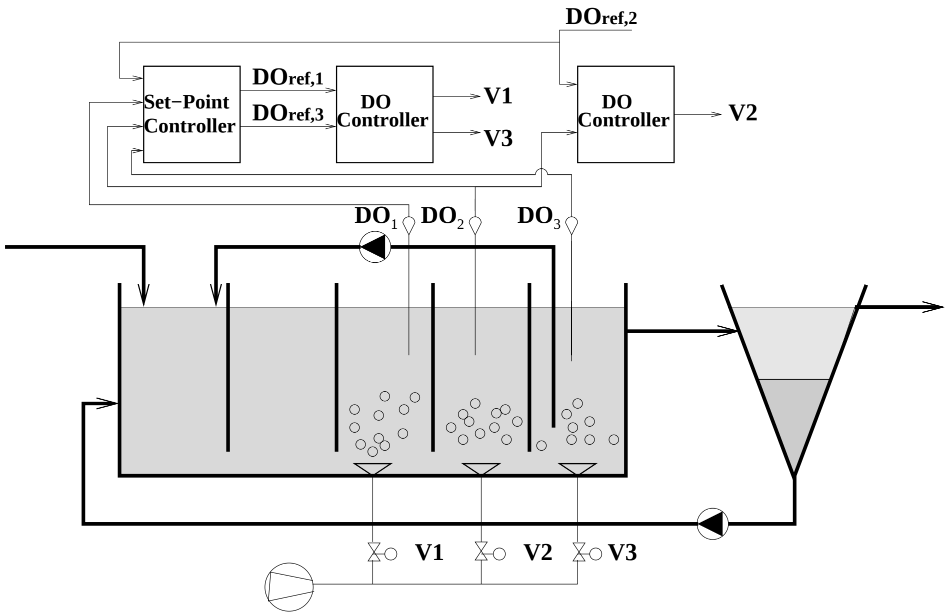


Figure 12. Simplified block diagram of the control strategy.

The strategy has been evaluated both using a simulation benchmark study and in an implementation at the pilot plant located at Henrikdal WWTP. In both cases, the strategy could save both energy and improve the treatment results (i.e. decrease the effluent concentration of nitrogen compounds). Pilot plant testing of the strategy in combination with simulation of the Henriksdal WWTP have shown that the energy for aeration may be reduced by the order of 30% and at the same time improving the treatment efficiency (i.e. decrease the concentration of nitrogen compounds in the effluent). This energy saving corresponds to 2.25 MSEK/year for Henriksdal WWTP (based on an electricity cost of 0.9SEK/kWh). The control strategy has been implemented in the prototype software.

A great advantage with the above approach is that only standard DO sensors are needed. If on-line ammonia sensors are available some alternative solutions have also been suggested. The key idea is then to feed back the actual treatment efficiency (in terms of ammonia concentration) and let the DO controller utilise this information. One interesting strategy is to measure the influent and effluent ammonia concentration as well as the influent flow rate and use this feed-forward information to approximate the aeration volume that is needed to get efficient treatment. If the desired aeration volume is larger than the currently used aerated volume, then more compartments corresponding to the nearest larger volume should be aerated. The DO set points are controlled supervisory utilising the effluent ammonium concentration measurements. Benchmark simulations of this strategy have confirmed that this combination of feed-forward aeration volume control and supervisory DO control could be an interesting alternative to pure DO control. Furthermore, it has a potential of significantly decreasing the aeration energy consumption while keeping, or even improving, the level of treatment performance. The strategy is presented in the Ph.D. thesis of P. Samuelsson, Uppsala University.

4.3.2 Economic efficient operation of a nitrifying activated sludge process

In order to run a wastewater treatment plant economically, operational costs such as pumping energy, aeration energy and dosage of different chemicals should be minimized. At the same time, the discharges to the recipient should be kept at a low level. Of course, minimizing the operational costs and at the same time treat the wastewater properly may lead to a conflict of interest that must somehow be solved. The main problem is how to keep the effluent discharges below a certain pre-specified limit to the lowest possible cost. Part of the answer is to design the control algorithms in such a way that the overall operational costs are minimized. This goal can be attained in different ways. As an example, the controller set points could be separately optimized or the cost could be minimized online by some control strategy, for instance model predictive control (MPC). In some countries, the authorities charge according to effluent pollution. A possible way to formulate the on-line minimization criterion in such a case is to use a cost function that takes actual costs (energy and chemicals) into account and at the same time economically penalizes the effluent discharges.

The choice of optimal set points and cost minimizing control strategies for an activated sludge process configured for pre-denitrification were evaluated by stationary simulations utilizing the COST/IWA simulation benchmark (BSM1). As manipulated variables (input signals) the internal recirculation flow rate and the flow rate of an external carbon source were selected. The impact of different nitrate cost functions on the location of the cost optimal operating point was examined. Figure 13 shows an operational map when the effluent nitrogen and effluent ammonia were penalized using one type of the examined cost functions that are piecewise linear but discontinuous. For each desired value (set point) of effluent nitrate concentration there is a cost-optimal point in the operational map corresponding to a certain value of the nitrate concentration in the last anoxic compartment. The cost-optimal set point of nitrate in the anoxic compartment depends on the choice of effluent nitrate set point, as well as the specific operational costs. The optimal level decreases with decreasing effluent nitrate concentration and with increasing energy costs (or decreasing costs for external carbon). In different operating points different control structure selections may be suitable. Clearly, the difference in the operational costs between an optimal and non-optimal set point may be large.

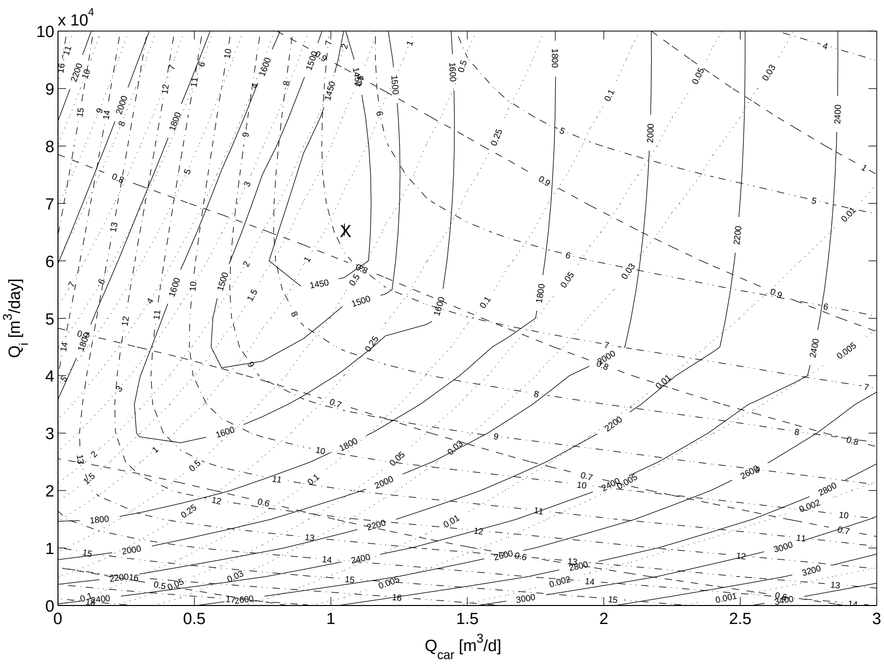


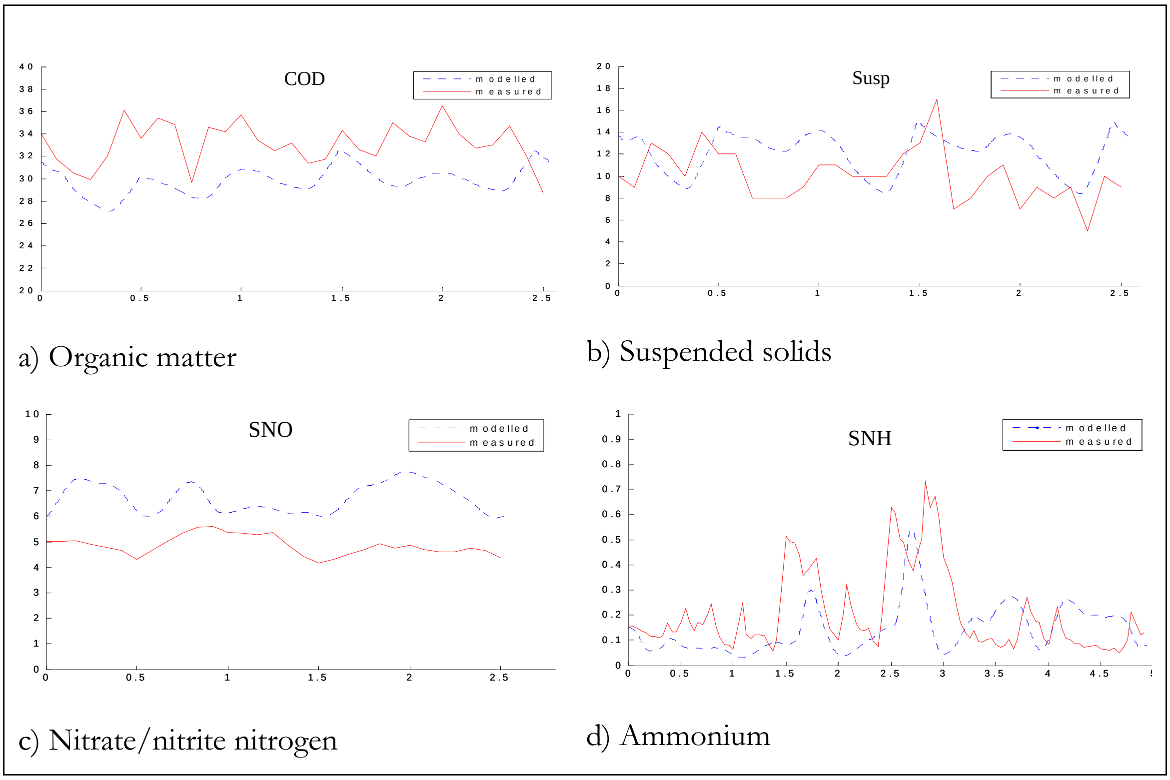
Figure 13. Stationary operational map for a grid of different values of external carbon dosage flow rate (Q_{car}) and internal recirculation flow rate (Q_i). Solid lines show the total cost in € including a nitrate-charge and an ammonia-charge, dash-dotted lines show the effluent nitrate concentration, dotted lines show the nitrate concentration in the last anoxic compartment and dashed lines show the effluent ammonia concentration. 'X' indicates the minimum-cost point.

Using this kind of fee functions in the total cost is a convenient way to achieve cost optimality for a certain set point of effluent nitrate. Minimizing this total cost function on-line using some automatic control strategy would be a good way to impose the importance of good performance via penalizing the effluent discharge into the control design. If the discharge of nitrogen and ammonia over a certain legislative limit is directly associated with a higher fee, this could clearly motivate the use of more advanced control strategies. Details can be found in the Ph.D. thesis of P. Samuelsson, Uppsala University and in [5] by P. Samuelsson, B. Halvarsson and B. Carlsson, cf. 6.2.

4.4 Simulation of biological treatment

4.4.1 ASM1 calibration

The ASM1 model[1] is used to describe the activated sludge process (ASP). The model was analysed and adjusted to fit the physical outline of the process at Henriksdal WWTP. A complete model of the ASP for the Henriksdal plant based on the COST Benchmark[2] has been established.



a) Organic matter

b) Suspended solids

c) Nitrate/nitrite nitrogen

d) Ammonium

Figure 14. Model performance (blue dotted) compared to measured values (red solid). In charts a-c independent validation data was used. Chart d shows model performance on calibration data. Ammonium modelled from validation data did not give satisfactory results.

The benchmark model in MATLAB/Simulink was used as a base and rebuilt and extended to fit the process of Henriksdal. ASM1 is used to describe the activated sludge process in the benchmark. The settler is modelled with a mass balance model where the settling velocity is described by a double exponential function. The parameters used in both models were calibrated to fit the wastewater treatment plant of Henriksdal. Three measuring campaigns were performed to provide data for calibration and validation of the ASM1 and to gather

[1] Activated Sludge Model No 1, International Water Association (IWA)

[2] COST, European Co-operation in the field of Scientific and Technical Research

information about the composition of the incoming wastewater. During one of the measuring campaigns a tracer test was performed in order to study the hydraulics of the biological treatment, including sedimentation basins. A specific dose of Li^+ ions were added at the inlet and its propagation through the basins was measured.

The measured data and information gained from the tracer study was used to develop and calibrate a model of the process at Henriksdal. After calibration the model obtained worked very well for modelling average values and also for modelling dynamic changes, cf. Figure 14.

4.4.2 Implementation in Simulink

This section summarizes the implementation of the simulator for the Stockholm Vatten Henriksdal (SVH) Water Treatment Plant Activated Sludge Process (ASP) and the numerical linearization procedure required to interface the model of the ASP with the MOO Agent for purposes of optimisation.

The model of the SVH ASP has been adapted from the COST Benchmark model and extended to meet the architecture of the specific plant. Parameter values, flow rates etc. used in the simulation are those resulting from measurement campaigns performed by IVL. The simulation model of the SVH plant ASP was implemented in MATLAB/Simulink. The resultant model involves over 2000 nonlinear differential equations.

The simulator of the SVH ASP refers to a 1-6-1 plant which involves 1 anaerobic, 6 aerobic and 1 anaerobic reactor in tandem for each of its 7 parallel paths. A single settler is common to all paths. Throughout, it is assumed that all seven parallel ASPs are identical and an identical control strategy is applied to all.

A MATLAB/Simulink flow diagram of the plant is shown in Figure 15. This model was used to investigate the behaviour of the plant for a variety of operating scenarios. All reactors are assumed to be identical but provision is made for different physical dimensions. Provision has been made to permit conversion of each reactor to aerobic or non-aerobic operation on demand to allow for different operational scenarios. Direct control of aeration in each aerobic reactor is performed by the existing field controllers (two-term PI with anti-windup) whose set points are specified by the DSS in accordance with the advanced control policy developed in the project. It is noted that the SVH simulator is flexible enough to allow for additional field controllers and can be easily adapted to any plant and more complex control schemes.

To permit ready visualisation of the behaviour of the plant, an array of numerical and graphical displays has been included in the SIM Agent. Results from the MATLAB/Simulink platform are deposited in data files that can be called by any of the Agents in the HIPCON System. The dynamic and static behaviour of the ASP was validated with experimental work performed on the actual the SVH plant.

An important function of the DSS is to allow for examination of different control policies with a view to quiescent optimality of the plant about any specified operating condition. In co-operation with the off-line Simulator, the DSS is a powerful tool for predicting overall plant behaviour to different operational scenarios as well as for training plant operators. The SCEN Agent that offers a ready interface for the user to examine different hypothetical operational scenarios and control strategies was developed and linked to the MATLAB / Simulation model.

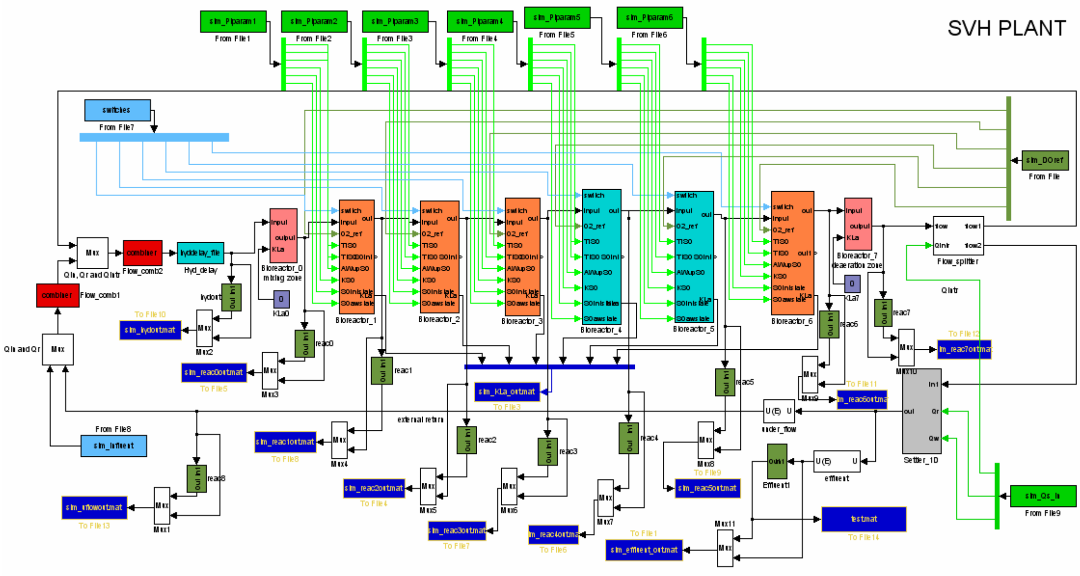


Figure 15. MATLAB/Simulink implementation of the WWTP.

Operation of the multi-objective optimisation Agent MOO depends on the results of plant simulation from which the sensitivity parameters are computed. Because the simulation model of the plant must be executed repeatedly many hundreds of times in the course of real-time optimisation, innovative techniques had to be developed in order to attain high computational speeds not normally possible with interpreters.

4.5 Environmental impact

4.5.1 Environmental models

Three LCI models, specific for the case study of Stockholm Water, were developed. The first two models are for the main commodities used in the process at Henriksdal, ferrosulphate ($FeSO_4$) used for chemical precipitation and electricity used for blowing air into in the activated sludge basins. The third LCI model is for the sludge treatment and disposal.

4.5.2 Model application

The environmental models of Stockholm Water are used on-line with data from the process, giving the operators continuous information on the environmental impact of running the process, cf. Figure 16 and Figure 17. The electricity model is also used together with the simulation model of the ASP, to investigate the environmental impact of different scenarios and to make environmental impact a part of the multi-objective optimisation.

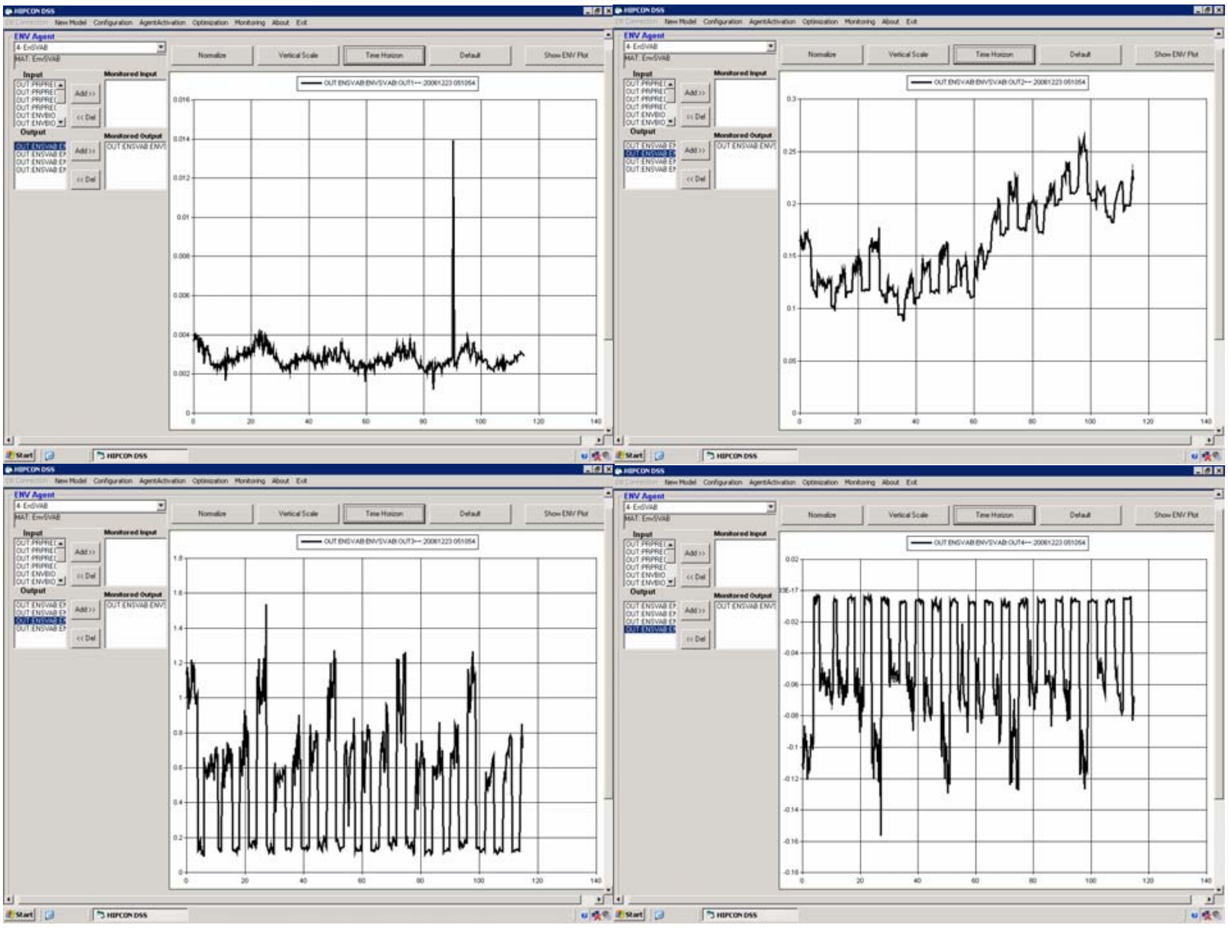


Figure 16. On-line environmental impact calculated by the HIPCON prototype. The plots start at 5 a.m. 2006-12-23 and cover a period of almost five days (unit on x-axis is hours). Upper left: AP, mol H^+/m^3 (the peak at the end is an outlier in data). Upper right: EP, kg O_2-eq./m^3. Lower left: GWP, kg CO2-eq./m^3 (cf. Figure 17). Lower right: WI, kg/m^3.

The models were also used with historical data from the WWTP process, representing the year 2003, in order to indicate the yearly environmental impact and to compare it with the environmental gain of treating the water. A normalisation method[3] was used to be able to convert the three categories AP, EP and GWP into one common unit. The environmental gain of treating the water was calculated by taking the difference of pollutants in the influent wastewater and the effluent treated water. It turned out that the environmental gain is considerably larger than the impact of the treatment process, at least for the impact categories used here. The sum of the normalised categories for the model results of the WWTP process is only about 2% of the gain, which only contributes to the EP category. Thus, with respect to the categories investigated here, the wastewater treatment process of this case study is environmentally sound.

[3] M. Erlandsson, 2002, Miljöbedömningsmetod baserad på de svenska miljökvalitetsmålen - visionen om det framtida hållbara folkhemmet, (in Swedish). IVL report B-1509, can be downloaded at www.ivl.se.

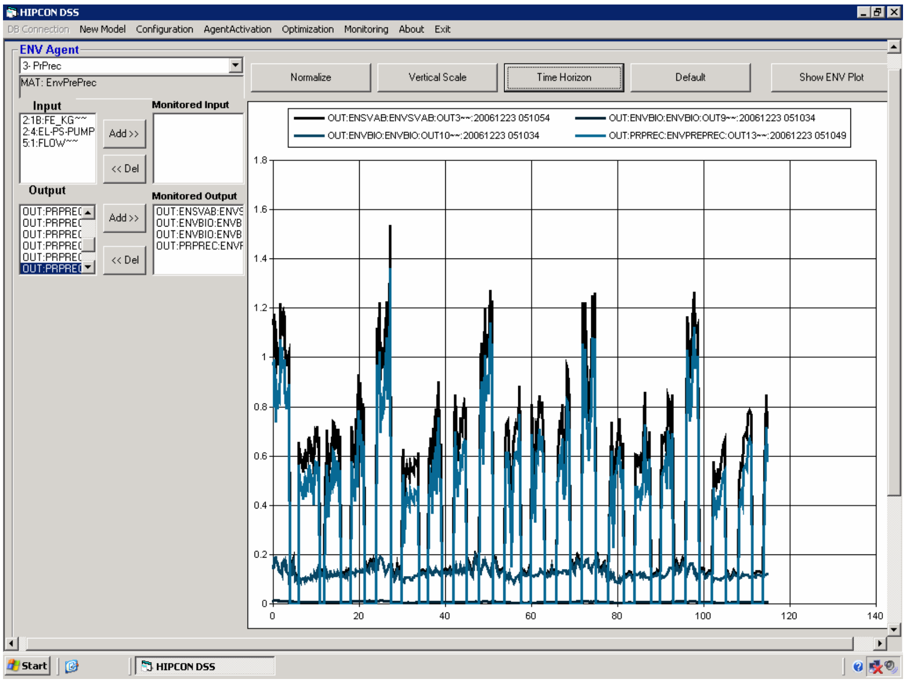


Figure 17. Detailed information of the on-line GWP by the HIPCON prototype. Cumulative GWP (black, cf. Figure 16). Major contribution comes from sludge treatment, primary sludge (turquoise with periods of zero value due to intermittent sludge flow) and bio sludge (blue). There is a minor contribution from the use of electricity in the ASP (brown).

4.6 Cost models

Table 1 shows the library of KPI for the SVAB Waste Water Treatment Plant (WWTP) with a breakdown of information on the associated cost drivers. Each of the cost drivers listed in Table 1 has been constructed and implemented in the HIPCON prototype. They have also been combined to construct the KPI, which are also implemented.

Table 1. SVAB: Henriksdal WWTP: Library of KPI's

Key Performance Indicator	Cost Drivers
TWQ: Treated Water Quality	Biological oxygen demand Total Nitrogen Total Phosphorous Ammonium Nitrogen
FSC: $FeSO_4$ Consumed	$FeSO_4$ in pre precipitation $FeSO_4$ in final precipitation Price of $FeSO_4$
ELC: Electricity Consumed	AS unit (aeration) nitrified water pump Sludge pump (recirc) Thickener centrifuges Sludge digestion mixer Dewatering centrifuges
BGO: Biogas Output	Total amount Amount & price of gas to Engine Amount & price of gas to Boiler Amount & price of gas to Vehicle Amount & price of gas to Torch
DSO: Digested Sludge Output	Disposal Price Amount of sludge produced

4.7 Multi-objective optimisation

The multi-objective optimisation in the WWTP case study is usually based on the simulation models for the pre-precipitation and/or the activated sludge process. These models are connected to other models (soft sensors, cost model, environmental impact models etc.) in model networks as exemplified below.

When the ASM1 model for the activated sludge process is to be used for optimisation, it must be approximated since it is highly complex, takes a long time to solve and does not have a closed form solution. An approach for linearization of the steady-state behaviour of the plant has been developed for this purpose that allows steady-state multi-objective optimisation of the activated sludge process. It is not possible to optimise with respect to the dynamic behaviour of the plant.

An example of a model network for multi-objective optimisation is shown in Figure 18. It includes the simulation models for the pre-precipitation and the activated sludge process in combination with a model for energy consumption of the aeration, an environmental impact model and two cost models. The environmental impact model and cost models account for the environmental impact and cost of pre-precipitation chemical and aeration.

The basis for the simple example used here to demonstrate multi-objective optimisation is that COD can be removed in either pre-precipitation or ASP. The $FeSO_4$ dose controls COD removal in the pre-precipitation, while the energy needed for aeration (by electric blowers) is dependent (among other things) on the COD removed in the ASP.

What is optimal with respect to greenhouse effect from LC perspective and/or cost? In order to investigate this, the model network shown in Figure 18 can be used. Note that this is a simplified example: phosphorous removal, sludge treatment and other important aspects on environmental performance are not included. Inclusion of these is not conceptually different than the example demonstrated here and only requires some extra models for sludge treatment cost etc.

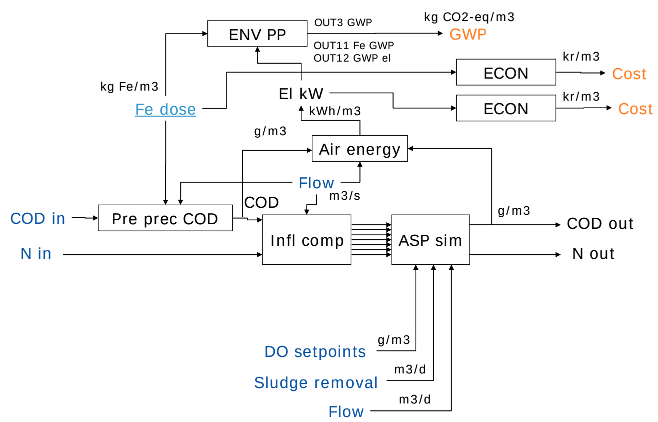


Figure 18. Model network for moo example. Objective functions have orange text. Fe dose is the single decision variable for this case.

Note that the network is deduced automatically (i.e. the input output relations of the models) from the configuration of the models to database tags. The model database includes a large amount of models but from the chosen objective functions the model network needed is automatically deduced. If the weights of the environmental and cost objective functions are varied systematically a pareto frontier can be plotted, cf. Figure 19. COD and nitrogen out from the ASP are approximately constant for all solutions on the pareto frontier.

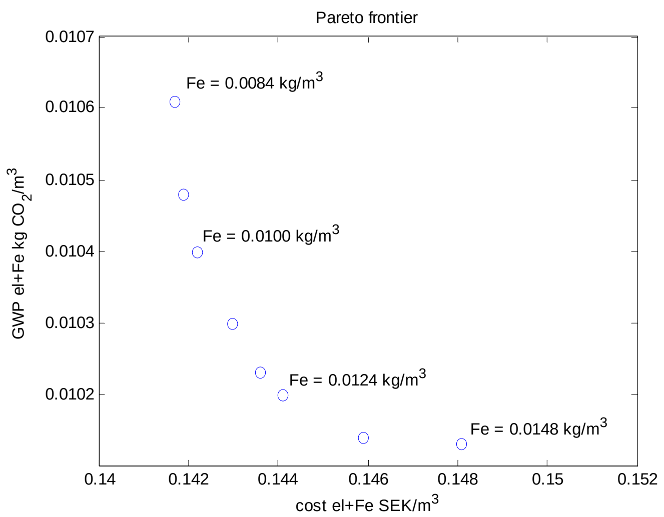


Figure 19. Pareto frontier for the moo example: the point Fe=0.0084 kg/m3 is for all weight to cost objective function while Fe=0.0148 kg/m3 is for all weight to environmental (GWP) objective function.

4.8 Other WWTP relevant results

4.8.1 Modelling approaches

HIPCON modelling approaches that are not described in detail in this report:

- Many models of WWTP's are bilinear (typical flow rate times concentration) and it is hence natural to use this information when defining the model structure. A detailed treatment of bilinear models with applications to WWTP's is presented in the Ph.D. thesis of M. Ekman, Uppsala University.
- An extension of the nonlinear modelling method (RPEM) used in section 4.2.1 is presented in by L. Brus et al [8](cf. section 6.2) where methods for initializing the estimation algorithms are derived. The estimation method is illustrated on modelling an anaerobic digestion process in [13] by L. Brus.

4.8.2 Control strategies

HIPCON control strategies that are not described in detail in this report:

- A state-of-the-art on Model Predictive Control (MPC) methods was conducted in the project. Some emphasis was given to strategies which integrates economical parameters. MPC for bilinear systems with applications to wastewater treatment (ASP) is studied in the Ph.D. thesis of M. Ekman, Uppsala University
- A biological reactor, for example an ASP, is an example of a multivariable system with several inputs and outputs. It is not obvious how to pair different inputs with different outputs when dealing with single input single output (SISO) controller. This problem is studied in the work of B. Halvarsson, P. Samulesson and B. Carlsson, [1] and [9], where also control structures are suggested.

5 Results of the steel manufacturing case study

5.1 Introduction

5.1.1 Process description

The steel manufacturing plant of SSAB in Oxelösund is outlined in Figure 20. The main process under study in HIPCON can be divided into i) iron manufacturing, including the coking plant, blast furnaces and the torpedo cars and ii) steel plant, including the LD-converter, TN-station, ladle furnace and the continuous casting machine.

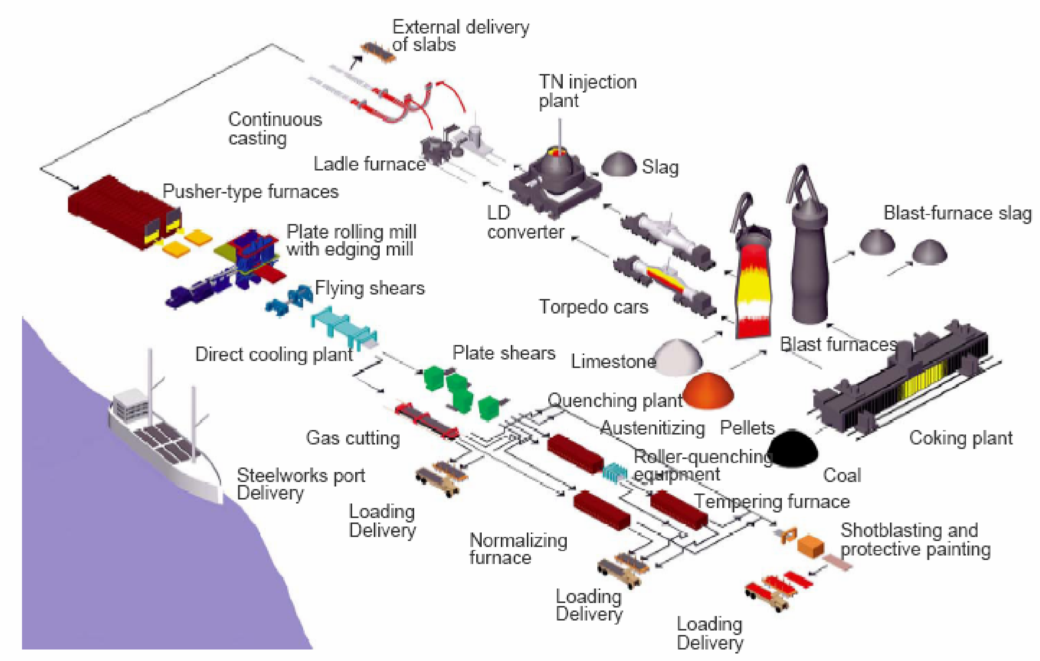


Figure 20 Process flow chart of the steel manufacturing plant at SSAB in Oxelösund.

In addition to the overall optimisation objective of HIPCON, special attention has been given to the sub processes desulphurisation (taking place in the torpedo cars) and LD-converter (Basic Oxygen Furnace, BOF), which is why they are described in more detail in the following overview of sub processes.

The **coking plant** converts black coal into coke, which is used as a reducing agent in the blast furnaces. An important by-product is the energy rich coke oven gas (COG), which is taken care of and used as fuel in several parts of the process at SSAB.

In the **blast furnaces** iron ore is converted into crude iron (hot metal), by the use of coal and coke as reducing agents and limestone as slag former. The blast furnace gas (BFG) is used as fuel in several parts of the process at SSAB.

There are eight **torpedo cars** of which six are in use at the same time. The other two are either being repaired or kept warm on standby. Each torpedo car can contain 325 tonnes of liquid iron and is coated on the inside with 90 tonnes of fireproof bricks. The liquid iron is cleaned, desulphurised, inside the torpedo cars in order to achieve an acceptable level of sulphur. Calcium carbide (CaC_2) is transferred into the liquid iron through a cast ceramic lance. The calcium carbide reacts with the sulphur and forms a slag, which floats on top of the iron because it is less dense than iron. When the concentration of sulphur is satisfactory the iron is poured into a ladle and transported to the LD converter. After the slag has been carefully withdrawn from the ladle, the hot metal in the ladle is charged into the LD converter.

The iron is converted into steel in an **LD**[4] **converter**. The capacity is 225 tonnes per charge. Once the hot metal temperature and chemical analysis of the blast furnace hot metal are known, computer charge models determine the proportions of scrap and hot metal, slag formers, lance height and oxygen blowing time. The primary purpose of blowing oxygen into the hot metal is to oxidise C, Si, Mn, P and V, and thus removing these elements, either in gaseous form or via the slag. At the end of the batch the hot metal has been converted into crude steel with a composition that does not vary too much between batches. It usually takes 35 to 45 minutes to treat a charge of hot metal in the LD converter. A reoccurring disturbance of the LD converter process is slopping. The slopping occurs when excessive carbon monoxide gas (CO) is formed during decarburization, which results in slag and hot metal foaming over the furnace opening. This phenomenon occurs every other day in different extent, disturbing the production and resulting in an excessive toxic gas leakage and loss of material.

The crude steel is tapped into a preheated ladle. During this procedure, deoxidisation agents like FeSi and Al are added to prevent high levels of oxygen. A rough adjustment of the steel composition is often made by **alloying at tap** of the LD converter.

In the two stations for secondary treatment, **TN station** and **ladle furnace,** the crude steel is further processed, e.g. alloyed and de-oxidised, for it to reach the requested final composition.

The **continuous casting** produces solid steel slabs from the liquid steel. Some of the slabs are further processed at SSAB in Oxelösund, while some are sent to another SSAB plant.

5.1.2 Case study objectives

The SSAB Oxelösund main case specific objectives were:

- Optimisation of the desulphurisation process, with respect to added chemical reagent and final sulphur content.
- Investigate the slopping phenomenon with the aim of predicting when it will occur, prevent it from occurring and control it when it does occur.
- Process modelling "coke to slab", to study e.g. the optimal process route and degree of refinement for different products, energy flows and environmental impact.

5.2 Desulphurisation optimisation

An analysis of the obtained S content after torpedo desulphurisation shows that the ordered value of S is sometimes exceeded. This is a consequence of the difficulty associated with predicting the process result. However, from histograms of the relative and absolute differences between ordered and obtained S content (Figure 21), it is clear that the batches where the S content is larger than the ordered is probably not the main problem in the desulphurisation process. Of the batches analysed 26% had S content that was 50% or more below ordered S content and 72% had S content that was 25% or more below ordered.

Due to the difficulty of predicting the process result, an on average far too large reagent dose has to be used in order to avoid many torpedo cars with S content over specification. It was

[4] LD is an abbreviation for the Austrian cities Lintz and Donavitz, where the process once was developed.

considered very likely that this leads to excessive reagent consumption and that an alternative approach for reagent dosage calculation have a potential to save resources in this process.

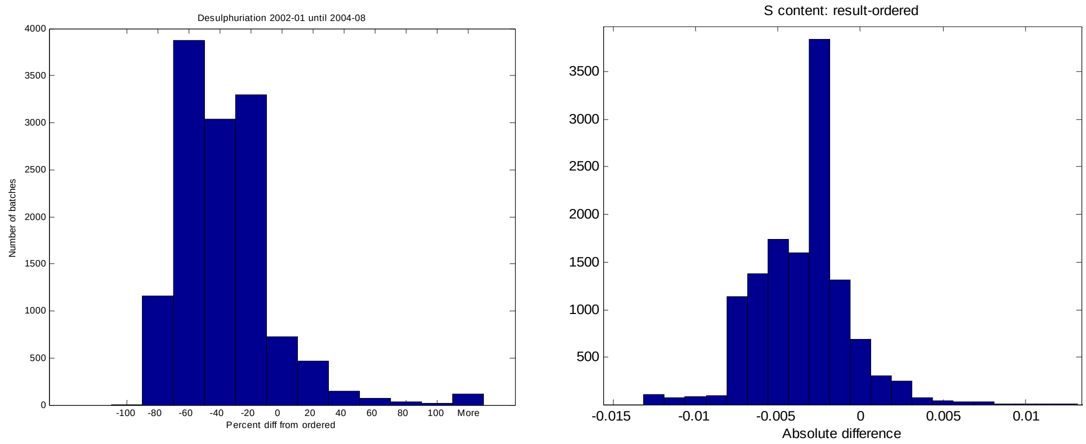


Figure 21. Histograms of the relative (left) and absolute (right) differences between ordered and obtained S content.

An initial analysis showed that many operational variables and metal properties, such as concentrations of some trace metals that were not considered in reagent dose calculation had an influence on the process and specifically the desulphurisation efficiency.

Different modelling approaches were tried with historical data from the process. The selected approach has a distinct advantage in that it allows dose optimisation to be carried out with a certain specifiable risk of exceeding S specification. The target S content for the dose optimisation calculation is chosen with consideration of model uncertainty and the selected risk of exceeding specification. With this probabilistic approach, the user can make his/her own trade off between risk of exceeding specification and reagent consumption, since a lower risk is always associated with higher reagent consumption.

The new dose optimisation approach was implemented and an operator interface was developed, see Figure 22. At the moment of writing this report, the approach has been in use at SSAB for 9 months.

The new dose optimisation strategy has been evaluated against two alternative approaches: (1) the dosing strategy used before the project was initiated (spring 2005) and (2) a dosing strategy based on a generic decrease of that dose (April 2006). The strategy was tested with different selected risk levels: 5% and 10%. The results are shown for treatments with 0.005% aim S content in Table 2.

Table 2. Results from test charges with 0.005% aim S content.

	risk level	**N**	**av. dose (kg)**	**av. obt. %S**	**av. rel. dose (kg CaC2/ton)**	**hit rate**
Ref spring 2005	-	785	1747	0.0035	6.89	96%
Ref April 2006	-	275	1633	0.0040	5.86	91%
HIPCON 5% risk	5%	69	1757	0.0024	6.39	100%
HIPCON 10% risk	10%	126	1465	0.0046	5.65	90%

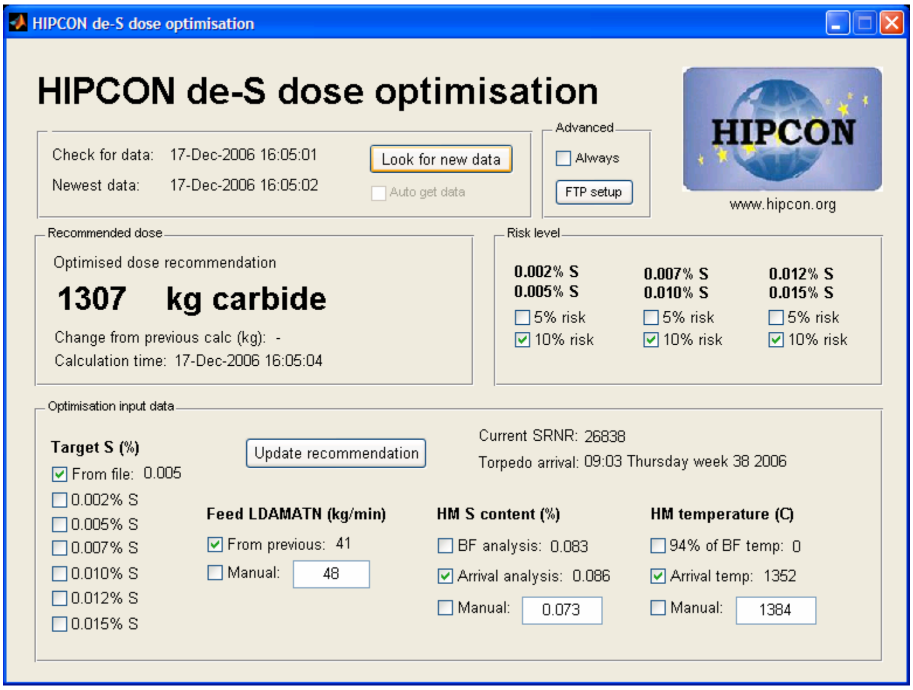


Figure 22. The HIPCON desulphurisation dose optimisation operator interface

It is clear that the reagent dose can be decreased while maintaining or even improving the number of treatments that are within specification. The general reduction of CaC2 dose from 2005 to 2006 increased the number of charges with S content exceeding specification from 4% to 9%. In the two HIPCON dose optimisation cases the percentage of charges exceeding specification is 0% and 10%.

The HIPCON dose optimisation strategy is superior both to the 2005 and April 2006 strategies. The explanation to this is the modelling methodology that takes into account many factors influencing desulphurisation efficiency that are not accounted for in the "non-HIPCON" approaches.

The economic consequences of implementing the proposed HIPCON dose optimisation strategy are shown in Table 3. Both the May and June versions, with different risk levels, show a huge improvement compared to the situation before HIPCON by saving 5 MSEK/y and 8 MSEK/y respectively.

Compared to April 2006 the 5% risk strategy means a lower risk of exceeding the aim S content but at the price of a higher cost. The June HIPCON strategy leads to the same risk as the April strategy but with almost 1 MSEK/year lower reagent costs.

Choosing the strategy to use, i.e. the risk level in the HIPCON dose optimisation is a strategic decision to be made by SSAB taking costs for exceeding %S specification into account.

Table 3. Economic consequences of implementing the proposed HIPCON dose optimisation strategies. Only reagent cost is included in the analysis. A CaC_2 price of 4700 SEK/ton has been used.

	CaC2 cost (MSEK/y)	Hit rate 0.005%aim	Hit rate 0.010%aim	Save reagent cost (MSEK/year)	
				Ref 2005	*Ref April 2006*
Ref spring 2005	46	96%	97%		
Ref April 2006	39	91%	85%		
HIPCON May 2006	41	100%	83%	4.8	-2.7
HIPCON June 2006	38	90%	83%	8.2	0.8

5.3 Steel converter process

5.3.1 Model based slopping monitoring

5.3.1.1 Background

Scrap, hot metal and slag forming agents are loaded into the LD converter and oxygen is blown through the lance, from above. The gas jet hits the metal bath at supersonic speed and oxidizes metal components such as iron, silicon, manganese and carbon.

The chemical reactions give rise to foam containing metal droplets, metal oxides (slag) and gas bubbles. This is favourable for the chemical reactions, due to the large contact area between the elements in the foaming slag and provides good conditions for the involved chemical processes. Furnace additions, changes of lance blowing position, oxygen flow through the nozzle and bottom gas flow rate are the main tools for the operator to control the slag formation. Problems arise when the foam level exceeds the height of the vessel and overflows, causing metal loss, process disruption, equipment damage and environmental pollution. This phenomenon is commonly referred to as slopping and has motivated a search for ways to maintain a suitable foam volume while preventing slopping from occurring. This task has, however, over the last decades proved to be rather challenging.

5.3.1.2 System structure

A warning system for slopping detection developed in the project is based on the off-gas flow rate, the raw microphone signal from the off-gas system and a pressure measurement. The sound signal is processed, to obtain an estimate of the slag level in the converter, based on the signal power at frequencies that are most significantly affected by the foam height. A model describing the relationship between off-gas flow rate, pressure and slag level estimate is updated recursively at each time instant. The output error is fed to a change detector to obtain a warning system with three alarm levels: green, yellow and red, indicating the persistence of slopping symptoms. Since foaming in the LD process depends on a number of slowly varying factors that are not measured, for example the temperature, the coefficients of the process model are estimated recursively in real time with an adaptive filter, Figure 23. The output estimation error of the adaptive filter is fed into a change detector that recognizes slopping as a drastic deviation from the normal process conditions and alarms the process operator.

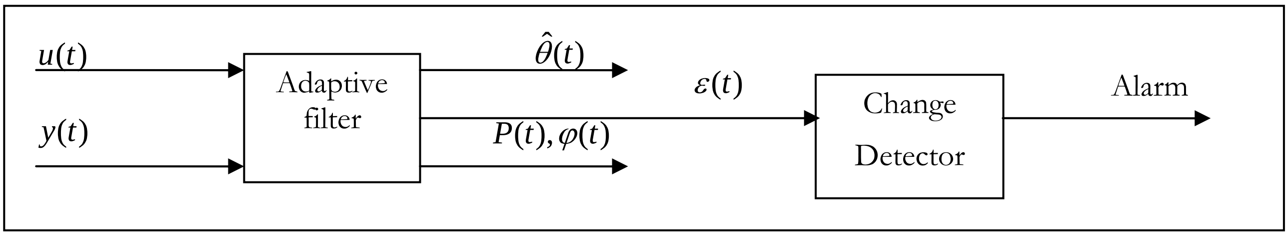


Figure 23. General principle of slopping detection: adaptive filtering and change detection.

To enable objective validation of an alarm system for slopping detection, an operator independent signal is needed to indicate slopping. A digital video camera is installed below the converter vessel. The basic principle of the camera signal processing is to segment the image frames into areas with falling slag and background, respectively. During normal operation the segmented image is black, while as slopping occurs falling metal will be captured and appear as white areas in the image frame. The ratio between bright and dark image pixels gives an indication of how severe the slopping event is.

5.3.1.3 System performance

A frequency domain model-based estimation algorithm validated on a water model is used to estimate the slag level from the microphone signal. The estimate of the foam height in the converter is compared to the sonic meter signal which is habitually used by process operators for slag monitoring, see Figure 24. The advantages of the mode-based estimate are

- More intuitive picture of the foam development in the vessel.
- A clear indication when slopping occurs in the steelmaking process.
- The selection of thresholds and algorithm parameters are facilitated, generating a more reliable and trustworthy slopping warning system.

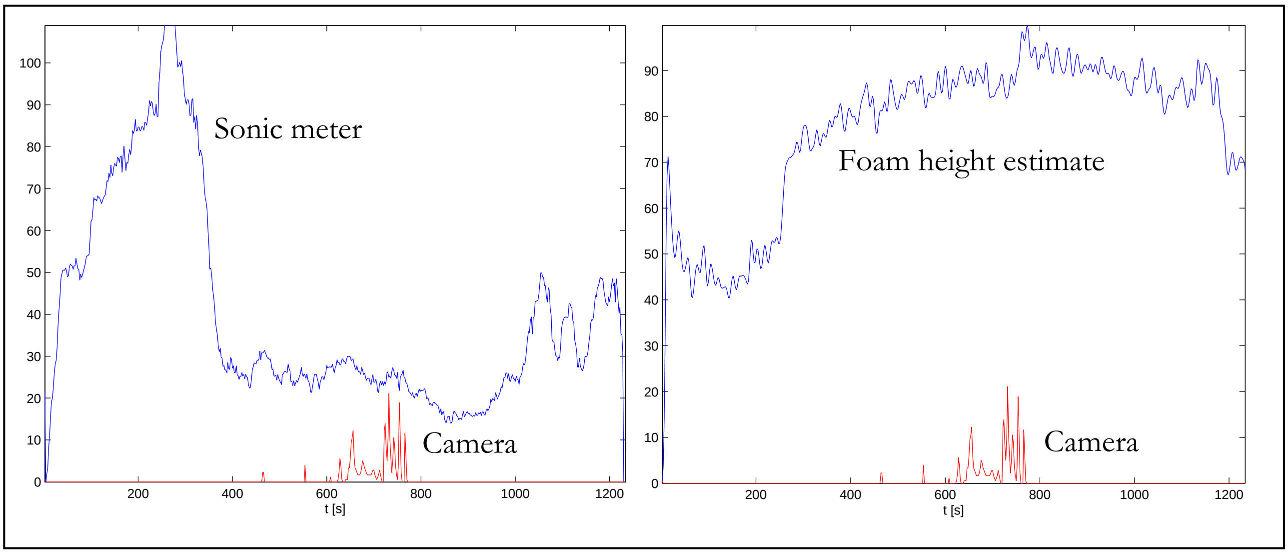


Figure 24. Indication of foam height based on a microphone signal. Left: The standard sonic meter signal. Right: An estimate of the foam height in the converter. Camera signal indicates slopping occurrence.

5.3.1.4 System evaluation

The experimental data were collected from the LD converter process located at SSAB Oxelösund during 100 charges. The data come from normal operation of the plant which means that slopping prevention and mitigation measures are taken by the operator. The latter is usually done by lowering the lance and oxygen flow rate. Thus it is important, when evaluating an alarm system, to ensure that the system reacts on the process phenomena and not on the operator actions. The system was validated by means of the surveillance camera below the vessel and found to provide correct slopping detection in 80% of the considered charges. The aim for the future is a system that automatically reacts on the alarms and performs standardized actions to prevent or mitigate slopping.

5.3.2 Dynamical modelling and estimation of cavity shape

5.3.2.1 Background

In the LD converter, oxygen is jetted onto the liquid iron surface from the top, through a lance, at supersonic speed. In the interaction area between the gas and the liquid, a cavity is formed, where some of the oxidization occurs. Understanding the effects of a gas jet impinging on a liquid surface would give more insight into the process behaviour and improve the efficiency of blowing, since lance position and oxygen flow are usually used as manipulated variables. The important parameters determining heat and mass transport at the interface and in the liquid are the interface shape, the width and depth of the cavity and the height of the peripheral lip. The cavity is also known to oscillate, both vertically and horizontally.

5.3.2.2 Water model

Since the steel bath is a hostile environment for performing experiments, a water model is usually used to study the liquid cavity of the LD-converter. In the water model, the molten steel is simulated by water and compressed air is used instead of oxygen. It has been shown that the physical properties of the two systems are similar. A significant advantage of the water model when it comes to shape estimation is that it is easy to collect visual information.

5.3.2.3 Mathematical model

Mathematical modelling of the cavity is important to extract valuable information from the image in the face of disturbance. Due to the difficulties of estimating the form of the cavity, researchers have previously concentrated on a few key parameters such as depth and diameter of the depression. On the contrary, for parameter, state estimation and control ends, physically motivated models have to be considered to provide sufficient process insight. This project focuses on a mathematical model stemmed from fluid dynamics that, combined with image processing techniques, is used to estimate the whole cavity profile and how it evolves in time.

5.3.2.4 Results

The cavity shape measurements are given in the form of images obtained by a video camera. To be able to compare the image to a mathematical model, the edge of the cavity is extracted from the measurement. A mathematical model of the cavity shape based on force balance explains well the observed cavity profile, see Figure 25. An observer-based image sampling algorithm has been developed and applied to the shape estimation problem with significant reduction of computation time and acceptable approximation accuracy. Proposing a sum of sine waves model to characterize the cavity oscillations, the variance of the depth and diameter estimates are decreased by 50%, compared to static case, using a small number of sine waves.

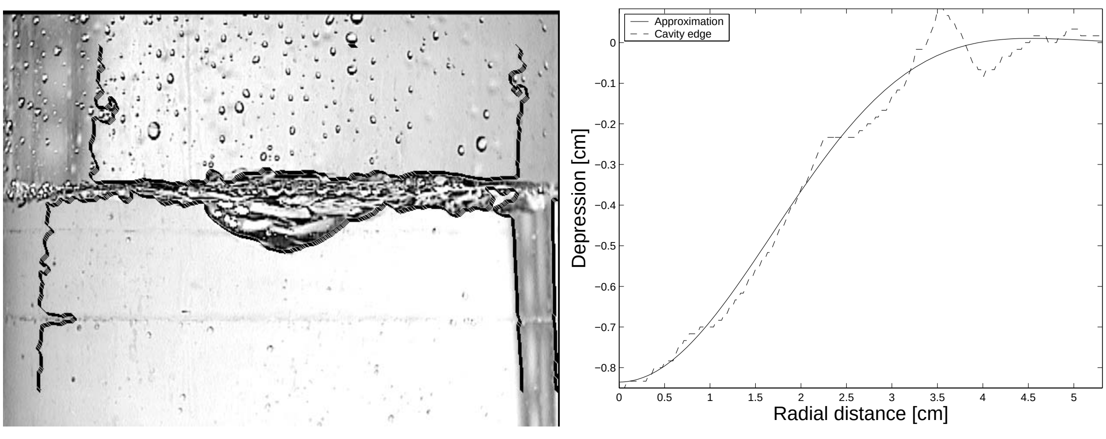


Figure 25. Left: Detected edges in the image. Right: Approximation of the cavity profile using a mathematical model based on force balance.

5.4 Plant simulation model

In order to be able to simulate and optimise economic and environmental performance of the full steel plant a model network was developed. Each model (each process step) is a model based on mass and energy balances and/or empirical relations. The complete plant simulation model (entire model network) covers the SSAB Oxelösund plant from coke plant to rolling mill. The focus is on the steel plant (BOF and alloying) and detailed mass balances for alloying elements and impurities have been developed for this part. The simulation model also describes all important energy flows in the plant, including electricity, energy rich process gases, oil, steam and hot water.

The plant simulation model can be used for:

– Scenario and what-if simulations.
– Multi-objective optimisation.

The model is a modified and extended version of a linear model of the SSAB plant in Luleå[5] that was built in the reMIND open source modelling environment[6]. The model can be exported in a so called MPS file (standard for linear programming models). Functionality was developed to read the MPS file in MATLAB and allow use of the model in the MATLAB environment. A special graphical user interface (GUI) was developed in MATLAB, into which the possibility to select freely the cost function (criteria for optimisation) and add extra equality constraints (called a scenario) was implemented, Figure 26. It is important to note that a cost function need not describe an economic cost. It can equally well be emissions or the use of a specific raw material that are minimised.

The optimisation problem to be solved every time the model is used is a so-called mixed integer linear programming (MILP) problem. Different solver alternatives were evaluated, including powerful solvers such as CPLEX and XA, but the current implementation uses a combination of in-house code and the interior point LP solver of the MATLAB Optimisation Toolbox. The in-house addition is used one level above the LP solver to handle integer variables.

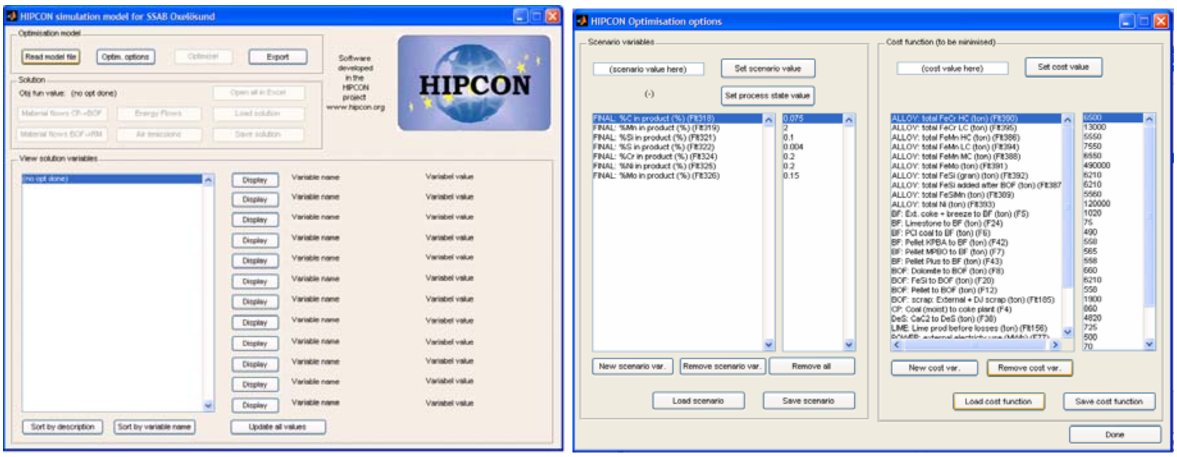


Figure 26. Plant simulation model GUI. Left: GUI at start-up. Right: The window for specification of optimisation options, i.e. scenario and cost function. Current scenario specifies the final composition of the steel. The cost function applied specifies raw material prices, thus inducing the optimisation to provide the most economical way, with respect to raw material cost, to produce steel with the specified composition.

[5] Courtesy of Mikael Larsson, Metallurgical Research Institute AB (MEFOS), Luleå, Sweden.
[6] reMIND, developed at Luleå University and Linköping University.

The optimisation/simulation results can be viewed numerically or graphically in the GUI or exported to Excel for further analysis. Some of the results from running the optimisation with the settings as specified in Figure 26 are shown in Figure 27 and Figure 28. The simulation model is fixed at a specified amount of produced steel corresponding to one charge of steel in the LD-converter. The model GUI was designed in cooperation with SSAB in order to make it easy to use for the SSAB staff.

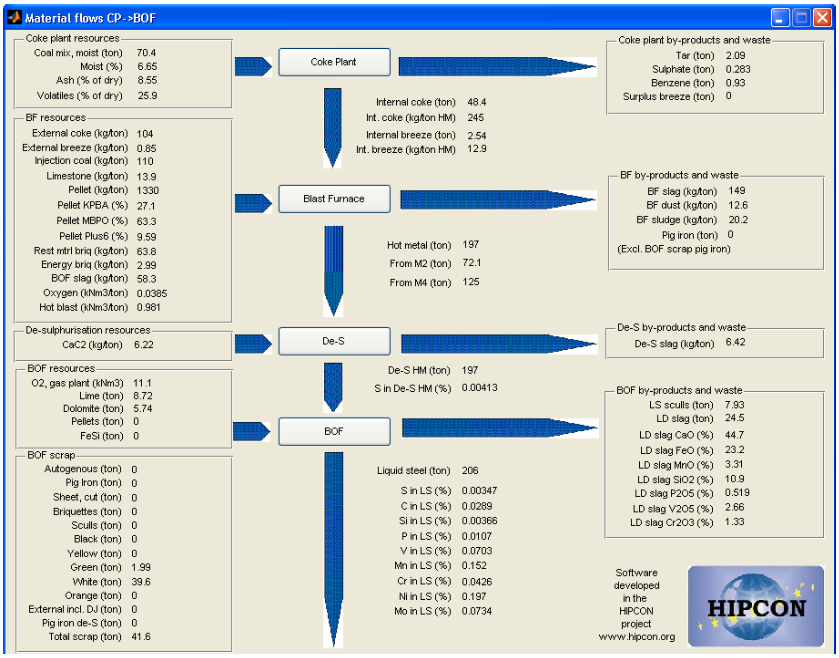


Figure 27. Optimisation results in the GUI. Material flows in the SSAB process, from the coke plant to the crude steel after the LD-converter (BOF). A similar window in the GUI gives the material flows of the alloying sections to the continuous casting. All values from a particular process section are easily exported to Excel by clicking on the section name in the GUI window.

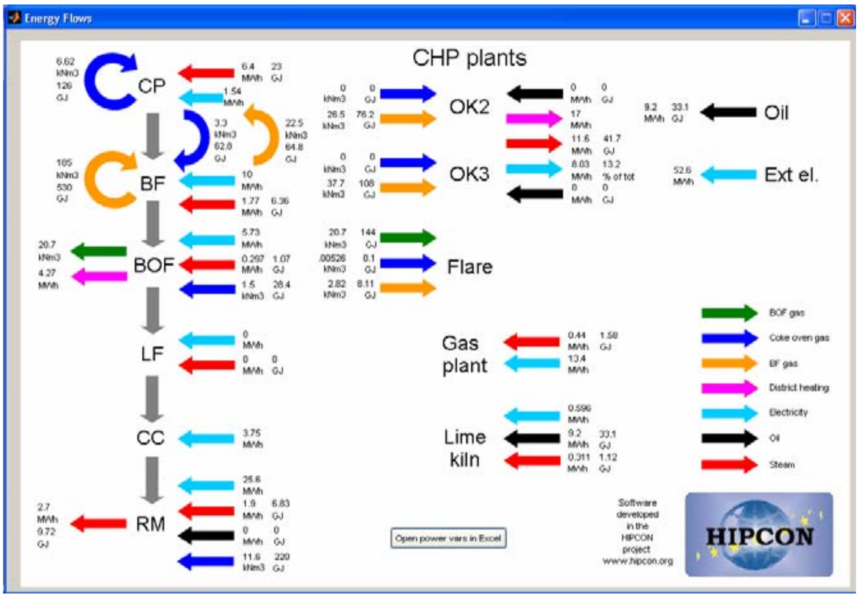


Figure 28. Optimisation results in the GUI. Energy flows from the coke plant (CP) to the rolling mill (RM), including the combined heat and power plants (CHP), the flare, the gas plant and the lime kiln. It is easy to compare the impact of different scenarios and cost functions on the allocation of process gases and the use of external electricity and oil. Note: in the model all of the BOF gas is flared, since this is the current practice at SSAB today.

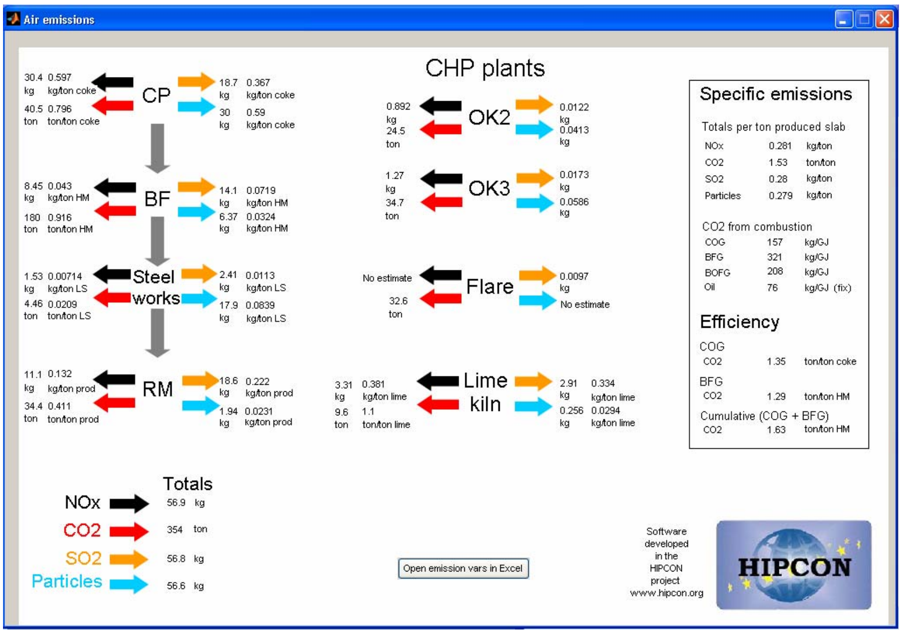


Figure 29. Optimisation results in the GUI. Air emissions from the coke plant (CP) to the rolling mill (RM), including the combined heat and power plants (CHP), the flare and the lime kiln. It is easy to compare the impact of different scenarios and cost functions on the emissions to air from different process sections.

5.5 Environmental impact

5.5.1 Environmental models

Regarding the number of commodities used in the process, the SSAB case study is far more extensive than the Stockholm Water case study. In total 30 LCI models to use at SSAB were developed, cf. Table 4. Transports of commodities to SSAB were modelled separately in order to differentiate these from environmental impact of production.

Table 4. LCI models of the SSAB case study.

Name	Model of	Name	Model of
Argon	Argon gas production.	FeSi	Ferro-silicon alloy production.
CaC2	Calcium carbide production.	FeSiMn	Ferro-silicon-manganese alloy production.
CaC2T	Calcium carbide transport.	IronPellet	Iron pellet production.
Coke_ext	Coke external production.	IronPelletT	Iron pellet transport.
Coke_extT	Coke transport (externally produced).	Lime	Lime production.
Coke_SSAB	Coke production at SSAB.	Limestone	Limestone production.
CokingCoal	Cooking coal production.	LimestoneT	Limestone transport.
CokingCoalT	Cooking coal transport.	Ni	Nitrogen alloy production.
DH_Ox	District heating from SSAB to Oxelösund municipality. Credit.	Nitrogen	Nitrogen production.
Dolomite	Dolomite production.	Oxygen	Oxygen production.
Electr_swe	Electricity production, Swedish average.	PCI	Production of coal for pulverised coal injection.
FeCr_HC	High carbon ferro-chrome alloy production.	PCIT	Transport of coal for pulverised coal injection.
FeCr_LC	Low carbon ferro-chrome alloy production.	PigIron	Pig iron (crude iron) production at SSAB.
FeMn_HC	High carbon ferro-manganese alloy production.	Scrap	Cooling scrap transport.
FeMo	Ferro-molybdenum alloy production.	Slag	Slag disposal.

5.5.2 Model application

The environmental models of SSAB are used with batch data from the process, which gives the operators current information on the environmental impact of running the process, in a similar manner as to that which was shown for the SVAB case study. They can also be used together with the plant simulation model, to investigate the environmental impact of different scenarios and to make environmental impact a part of the multi-objective optimisation.

In addition to this, the models have also been used to compare the environmental impact of the different process sections at SSAB. This is illustrated in Figure 30, with an example using production data from the year 2005 as inputs to the models. Results are given for the GWP category, which is very important to the case study due to the recently incorporated carbon emission trading system. Even though the direct emissions of CO_2 at SSAB are the dominating the contribution to GWP, the LCI-impact is not negligible. The LCI-impact is most likely underestimated, due to inevitable gaps in data.

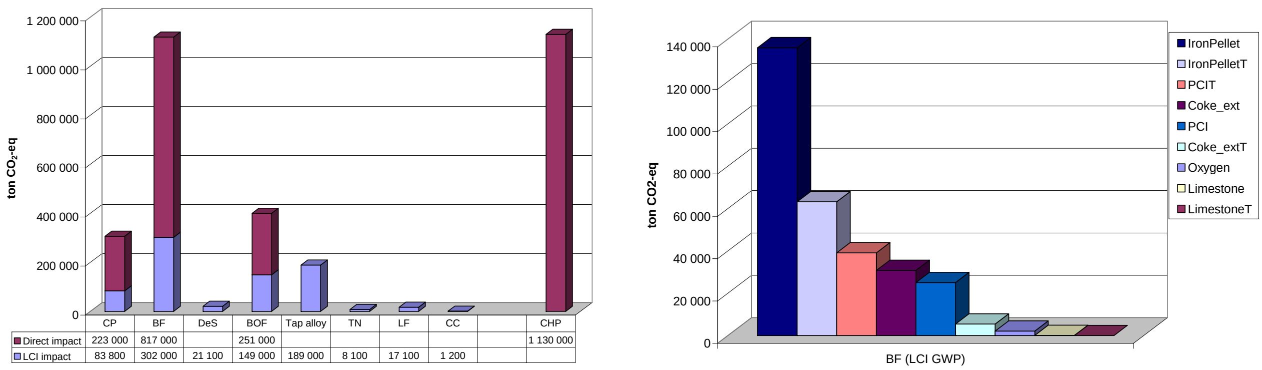


Figure 30. Left: GWP of the SSAB process, coke plant (CP), blast furnaces (BF), desulphurisation (DeS), basic oxygen furnace (BOF), alloying at tap (Tap alloy), TN station (TN), ladle furnace (LF) continuous casting (CC) and combined heat and power plants (CHP). Right: Details on LCI impact associated with the blast furnaces.

5.6 Social indicators

The applicability of social indicators in the context of holistic integrated process management has been investigated. The specific goal was to identify social parameters, which are relevant and possible to use at the case studies. The method developed in this work is suitable for interpretation of the relationship between the selected process variables and the social indicators.

Possible social indicators were discussed with key personnel at both case studies. The conclusions of those discussions are that

- Social indicators can be used both to describe both the **input to and the outcome of the process in social terms**, e.g. how the social dimension is affected both in positive and negative terms.
- **Social indicators as input to the process** have shown to be of great interest to the companies of the two case studies. In both companies the social indicators relating to the manning, the competence and the work ability of the staff are perceived as most important to the outcome of the process both in terms of productivity, quality and probably also environmental load from the process.

- There is a limited interest in the **social dimension when measured as outcome** such as child labour or discrimination. There is however an interest in these issues from both companies and these issues are already dealt with in other ways. The main strategy is to deal with the social dimension in the purchasing process, through policies and demands on e.g. the companies that supply raw materials. As long as SSAB's and Stockholm Water's clients and owners are content with this strategy, it will be applied.

For SSAB, staff competence, years of employment and age were compiled and related to number of slopping events, amount of steel with quality deficiencies, number of re-blowings and tapping temperature.

Modelling based on these parameters and indicators showed that:

- The social indicators are highly correlated i.e. in general older employees with many years at SSAB have high plant and metallurgy competence.
- The relative number of slopping events per shift is lower for employees with high values on the social indicators.
- The number of re-blows per number of treated charges of a shift is lower for employees with high values on the social indicators.
- The social indicators have no correlation to the number of charges treated per shift.
- The social indicators have no correlation to occurrences of quality deficiency in the final steel.
- No correlation was found between the social indicators and deviations from target value of the pre-sample temperature or tapping temperature.

A similar study was initiated at the WWTP case study, but after the initial interviews it was decided that evaluation of the social indicators should not be carried out for Stockholm Water. The relation between e.g. staff competence and the outcome of the water treatment process was expected to be very weak. Other factors such as amount of rain and snow and the long lag-time between cause and effect were considered to be of greater importance.

5.7 Cost models

The cost models for the SSAB case study consist of KPI models that have been developed for each sub-process in the plant. The Oxelösund plant has been divided into eight conceptual sub-processes, or units:

1. CP: Coke Plant
2. BF: Blast Furnace
3. DS: Desulphurisation Torpedo Cars
4. LD: LD Converter
5. AL: Alloying in Ladle
6. TN: TN Station
7. SU: Ladle Furnace
8. CC: Continuous Casting

For all the sub-processes, the KPI to be considered can be divided into the five categories listed in section 3.2.2, but not all of these categories are relevant to all units. For example, energy costs have only been considered at the Ladle Furnace SU stage. A summary of all KPI that have been implemented in the HIPCON prototype is shown in Table 5.

Because evaluation of these models requires up-to-date prices, a separate database for prices has been developed, along with a user interface to allow easy updating of price information.

Table 5. SSAB: Oxelösund steelworks library of KPI's. HM = Hot Metal, CS = Crude Steel.

Unit	KPI	Comment
1:CP	RMCP: Raw materials	Manly the different types of coal
	PVCP: Product value (Coke)	Market value for coke
2:BF	RMBF: Raw materials	Mainly pellets, limestone, coke and coal
	PVBF: Product value (HM)	Market value for (un-desulphuried) pig iron, scrap price
	BPBF: By-product disposal	The slag production is affected by how the process is controlled
3:DS	RMDS: Raw materials	$CaC_2$is a major cost, depends on HM sulphur content
	PVDS: Product value (HM)	Market value for desulphurised pig iron, scrap price
	BPDS: By-product disposal	Amount of slag is related to the amount of added CaC_2
4:LD	RMLD: Raw materials	Includes process gas (O_2, Ar/N_2), slag formers, coolants and fuel
	PVLD: Product Value (CS)	Difficult to evaluate, but market value is estimated
	BPLD: By-product disposal	Depends on the process e.g. slopping, slag forming, HM composition
5:AL	RMAL: Raw material costs	The major (bulk) alloying is made at this stage
6:TN	RMTN: Raw material costs	Alloy adjustment, coolants, fuels and process gas (Ar)
	BPTN: By-product disposal	Sulphur: directly related to the use of synthetic slag, which is related to the steel composition before and aim-composition after treatment
7:SU	RMSU: Raw material costs	Alloy adjustment and process gas (Ar)
	ECSU: Energy Consumed costs	Heating, stirring and vacuum degassing
	BPSU: By-product disposal	Directly related to the usage of synthetic aluminium (slag)
8:CC	PVCC: Product Value (Steel)	Can be related to market value for slabs

5.8 Multi-objective optimisation

The simulation model for the SSAB Oxelösund plant, described in 5.4, can be used in the multi-objective optimisation framework developed in the project and implemented in software prototype. In this manner, the resource consumption and direct emissions that are part of the plant simulation model can be used together with models for environmental impact form life-cycle perspective and cost models.

Environmental impact models have been specifically developed for this purpose, since the models used for continuous monitoring of environmental performance in the plant, described in 5.5.2, can not be used together with the simulation model due to a different way of specifying consumption of some raw materials in the real-time database and the model. The environmental impact models for use with plant simulation model also account for direct emissions of CO_2, NO_x, SO_2 and PM10 that are estimated in the simulation model but not available as real-time measurements for monitoring.

A special GUI has been developed to enter and change raw material prices in the HIPCON database so that economic objective functions in the optimisation are always based on current prices. Cost models are available for most raw materials described by the plant simulation model but investment and labour costs are not accounted for. Consequently, the multi-objective optimisation framework for the SSAB Oxelösund plant is an operational and tactical planning tool rather a strategic decision support tool.

5.9 Other steel manufacturing relevant results

Latent variable modelling work was performed to increase understanding of slopping phenomena, i.e. to identify risk factors for slopping in terms of metal composition or operating practices. The model result can be seen as a slopping risk indicator and describes properties of the materials that increase slopping risk, not that necessarily cause slopping.

6 Dissemination

6.1 Industrial dissemination

Throughout the project an industrial reference group (IRG) has followed the project. The IRG has served the project in two aspects:

- Contribute and give comments on the technical development of the software
- Initiate applications at their own production plants using the results derived from the HIPCON-project

The members of the IRG that contributed to the project in various ways are:

- John F. O'Reilly
  Head of Technology
  Rio Tinto plc
- Mr. Raymond Jack
  Business Transformation Director
  Scottish Power
- Danny Lawrence
  National Environment Manager
  Lafarge Cement UK
- Henrik Kloo
  Manager, Environmental Science
  Volvo Technology
- Dr. Guido Smits
  R&D Leader
  Corporate R&D
  Dow Benelux NV
- Philip Jonathan
  Principal Statistician
  Statistics and Risk Group
  Shell Global Solutions
- Mr. Matti Kleimola
  Group Vice President, Technology
  Wartsila
- Roine Morin
  Head of Environmental Affairs
  SCA Graphic Sundsvall AB
- Alastair Bissett
  Development Methods Manager
  Federal Mogul Friction Products Ltd
- Gunnar Eriksson
  Environmental Manager T.Q.5
  Scania
- Alvaro Garriga Meco
  Senior Consultant, Technology Unit,
  Centro Tecnologico, CTR
  Repsol YPF
- Dr Ciro Nicolai
  Senior Adviser to the Chief Technical Officer
  Finmeccanica Group

In the technical direction of the project the IRG has contributed in a very constructive way. Since the IRG represents a big variety of industrial processes they gave useful feedback in the very beginning of the project in terms of the necessity of the applicability on continuous, semi-continuous and batch processes. In the end of the project it was also clarified that the consortium need to think in terms of turning the prototype into a commercial software to get acceptance from the industry to use the product in full scale. Especially the capacity in terms of maintenance, installation guaranties, updates etc. was mentioned. Their feedback in these items has resulted in outlining a business plan for a new company with the task to take the research results, develop them further and achieve commercialisation.

The second purpose for the IRG was to act as potential end-users as the results evolved throughout the project. Some industries have been very proactive in this perspective. At the Federal Mogule a project was initiated as a feasibility study already during the second year of HIPCON. Finmeccanica, Volvo, Repsol, RTZ and other associated industries have been following the project with a big interest and different project start-ups are in progress.

Through different national and international seminars other industries outside the IRG have shown a big interest in the HIPCON approach. Projects on controlling wastewater treatment plants in Rumania have started. In a workshop in India the pharmaceutical industry showed a big interest in these results and is planning to start projects implementing the HIPCON-software.

6.2 Scientific publication

The following scientific papers and conference presentation describe work from the HIPCON project.

1. *Applications of coupling ananlysis on bioreactor model*s
   by B. Halvarsson, P. Samuelsson and B. Carlsson.
   Proceedings of 16th IFAC World Congress, Prague, July 4-8, 2005.
2. *Cavity Depth and Diameter Estimation in the Converter Process Water Model*
   by M. Evestedt and A. Medvedev.
   AISTech Iron and Steel Technology Conference Proceedings, September 15-17, 2004, Nashville, Tennessee, Vol. 1, pp. 763-771
3. *Cavity shape dynamical modelling and estimation in a water model of the steel converter process*
   by M. Evestedt and A. Medvedev.
   Accepted for publication in the proceedings of the International Symposium on Advanced Fluid/Solid Science and Technology in Experimental Mechanics, September 11-14, Japan, 2006.
4. *Control of the aeration volume in an activated sludge process.*
   by M. Ekman, B. Björlenius and M. Andersson.
   Water Research. - 2006 (62) , s. 1668-1676
5. *Cost-Efficient Operation of a Denitrifying Activated Sludge Process*
   by P. Samuelsson, B. Halvarsson and B. Carlsson.
   Water Research, accepted for publication.
6. *Desulphurisation dose optimisation*
   E. Furusjö and M. Thorén
   Manuscript
7. *Gas Jet Impinging on Liquid Surface: Cavity Shape Modeling and Video-Based Estimation*
   by M. Evestedt and A. Medvedev.
   IFAC World Congress, Prague, July 4-8, 2005
8. *Initialization and Black-box Identification of Nonlinear ODE Models Applied to Laboratory Plant Data.*
   by L. Brus, T. Wigren and B. Carlsson.
   Submitted for publication to *IEEE Trans Control Systems Technology*, (2006).
9. *Interaction analysis and control structure selection in a wastewater treatment plant model*
   by P Samuelsson, B. Halvarsson, and B Carlsson.
   IEEE Transactions on Control Systems Technology. - 2005 (13) : 6.
10. *Mining the causality relationships of the pre-precipitation stage of a wastewater treatment process using self-organizing networks*
    by A. Stathaki and R. E. King.
    Accepted for publication in Int. Journal of the Environment and Pollution, 2007
11. *Model-based cavity shape estimation in a gas-liquid system with nonuniform image sampling*
    by M. Evestedt and A. Medvedev.

1st International Conference on Computer Vision Theory and Applications, February 25-25, Portugal, 2006.

12. *Model-based slopping monitoring by change detection*
by M. Evestedt and A. Medvedev.
Accepted for publication in the proceedings of IEEE International Conference on Control Applications, October 4-6, Germany, 2006.

13. *Nonlinear identification of an anaerobic digestion process*
by L. Brus.
IEEE International Conference on Control Applications (CCA), Toronto, Canada, August 29-31 2005, pp. 137-142.

14. *Prediction of Wastewater Pre-precipitation Variables using Self-Organizing Networks*
by P. Isaias, S. Nilsson, A. Stathaki and R. E. King.
Presented at the 13th IEEE MED'05 Conference in Limassol in June, 2005

15. *Reduced energy consumption and improved nitrogen removal by using more effective aeration.*
by M. Ekman and B. Björlenius.
Vatten. - 2006 (40) : 10

16. *Stationary behavior of an anti-windup scheme for recursive parameter estimation under lack of excitation*
by M. Evestedt and A. Medvedev.
IFAC World Congress, July 4-8, Prague, 2005.

17. *Stationary behavior of an anti-windup scheme for recursive parameter estimation under lack of excitation*
by M. Evestedt and A. Medvedev.
Automatica, January, 2006.

18. *Steel Converter Process Control with Cooling Additives*
by B Sokolov, A Shepeljavyi and A Medvedev.
6th IFAC Symposium on Nonlinear Control Systems NOLCOS2004, September 01-03, 2004 Stuttgart, Germany, pp. 1529-1534

19. *A Decision Support System with Distributed Agents for Large-Scale Process Control*
by A. Prayati, A. Stathaki, E. Furusjö and R. E. King
submitted for publication

The following PhD Theses have been presented at Uppsala University:

- *Control of Nitrogen Removal in Activated Sludge Processes*
  by P. Samuelsson.
- *Modeling and Control of Bilinear Systems, Applications to the Activated sludge Process.*
  by M. Ekman.

7 Outlook

Industries from the Industrial Reference Group (IRG) and other associated industries have started projects that implement the HIPCON concept as a tool for their production management. These new projects will play a major role in kicking off the development of future business and applications. As the projects develop and references are being created, members of the HIPCON consortium are working on setting up a new company to commercialise the results and to meet the future demands on software development, service and support needed for fully functional installations. The work is organised by Ian Napier, HIPCON exploitation manager, together with Jonas Röttorp who are now planning the next steps for successful commercialisation of the HIPCON results and setting up the new company for exploitation. The new company with associated partners will be the platform for reaching new projects and applications.

The HIPCON project results have delivered findings that show measurable benefits for the two companies where the two case studies were conducted, and because of the generic nature of the products and services developed, the results will be of benefit to other companies in the same industry sectors (Steel production and Water treatment) and should also be transferable to other process industries. The products and services that are exploitable consist of software packages and also developed methodology. There will also be support services for: assessing where in the process the products can be used; installation; testing; training; updating the products. The exploitation work is currently in progress and consideration is taken of the following topics:

- Description of products and services for commercialisation
- Quantification of advantages
- Basis for decision to commercialise selected products and services
- Commercial options and best routes for implementation
- How the commercialisation will be conducted
- Dissemination of findings
- Market demand and competition
- Time schedule

On the research agenda the consortium has realised the future needs on robustness and adaptivity for these types of intelligent process management systems. This research area will be very important to meet the industrial demands on reliability and high accessibility of advanced software systems for process control.